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Inventory Behavior, Demand, and Productivity in Retail

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Abstract

This paper studies the factors underlying the heterogeneity in inventory behavior and performance across retail stores. We use a dynamic model of multi-product retailers and local competition to estimate store productivity and consumers' perceived quality of the shopping experience, and we analyze their relationship with inventory behavior and product variety. Using novel and detailed data on Swedish stores and their products, we find that stores learn from demand to improve future productivity. Store productivity is the main primitive that increases inventory turnover and product variety, and this increase is larger for stores with already high inventory turnover. Stores in small markets with intense competition from rivals have higher inventory turnover. Consumers in large markets and markets with large investments in technology benefit from a broader product variety. Counterfactual experiments show that the increase in inventory turnover due to innovations in productivity is three times greater when uncertainty in demand is reduced by 30 percent. Our analysis highlights important trade-offs between productivity and demand that allow retailers to reach high levels of inventory turnover and offer a broad product variety to consumers.

Keywords: productivity; inventory performance; supply chain management; product variety
JEL Classification: L11, L13, L25, L81, M21

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1 Introduction

The core of retail businesses is buying products from wholesalers and delivering them to consumers in a timely manner with quality. Inventories increase shopping quality for consumers who value accessibility and variety on the shelves but are costly to adjust and hold in stock. Inventory stands for a high share of retailers' total assets and vast resources are spent on inventory management.[1] The total inventory and inventory-to-sales ratio in U.S. retail for 2018 are estimated \$509 billion (an increase of 6.6 percent from the previous year) and 1.26 (a decrease of approximately 4 percent). At the same time, labor productivity increases 2.9 percent per year on average, but there are large differences across subsectors.[2] Inventories have received extensive attention in the literature, for example, the relationship between inventories and firm performance, price variation and market power when demand is uncertain, and GDP fluctuations.[3] However, there are still open questions about what explains the large observed heterogeneity in inventory behavior and performance across stores in the same retail industry. Our goal is to analyze the role of store productivity and demand shocks related to consumers' shopping quality in store performance, inventory behavior, and product variety.

We provide an empirical model to recover store's total factor productivity and consumers' perceived shopping quality that are used by stores in the decision process but are not observed by researchers or recorded in the data. In our model, stores offer multiple products and managers use information about consumers' determinants of store choice to strategically decide inventory, investment, labor, and the number of products to maximize long-run discounted profits. We estimate the model using novel and detailed data on every product category in Swedish retail stores between 2003 and 2009. Such rich data on products, inventory, inputs, and outputs for each store-year observation have, to the best of our knowledge, not been used in services industries before.

Using the estimated model, we analyze two crucial aspects for store managers. First, we investigate the underlying theoretical primitives behind heterogeneity in inventory behavior and performance (i.e., inventory turnover defined as the cost of goods sold over inventory) and in product variety. Second, we simulate a number of counterfactual experiments to explore trade-offs in optimal responses to hypothetical innovations in productivity and shopping quality. Our study has strong implications for management practices, as it relates directly to the hands-on decisions of store managers. A main strength of the proposed framework is that it provides information about optimal managerial decisions and highlights the transmission channels from changes in levels and

[1]Inventory was approximately 21 percent of total assets for the average U.S. public retailer in 2011 (Gaur et al., 2014). The carrying cost of inventories represents approximately 25 percent of the value of inventories and includes the capital cost, storage space cost, inventory service cost, inventory risk cost. To avoid stock-outs, retailers spend more money on financing inventories than on advertising.

[2]www.census.gov/economic-indicators and www.bls.gov/lpc

[3]For early research on the role of inventories, see Working (1949), and Brennan (1958). There is an extensive literature in operations management and operations research that begins with models such as economic order quantity (EOQ), newsvendor inventory, more complex theoretical models (e.g., Bernstein and Federgruen, 2005; Cachon and Terwiesch, 2005; Jerath et al., 2017) and continues with empirical research on inventory performance and product variety using firm-level data (e.g., Liberman et al., 1999 Lieberman and Demeester, 1999 van Ryzin and Mahajan, 1999; Gaur et al., 2005; Rumyantsev and Netessine, 2007; Rajagopalan, 2012; Cachon and Olivares, 2010; Raman, 2012; Shockley and Turner, 2015; Gaur et al., 2014; Alan et al., 2014; and Cachon et al., 2018). In industrial organization and marketing, there is a growing literature that uses rich economic modeling and high-frequency data for a set of products and stores to evaluate the relationship between inventory and pricing in retail (e.g., Aguirregabiria, 1999; Hendel and Nevo, 2006; Matsa, 2011; and Seiler, 2013). In macroeconomics, there is a vast literature on the relationship between inventories and business cycles (e.g., Blinder et al., 1981; Blinder and Maccini, 1991; Ramey, 1989; Ramey and West, 1999; and Khan and Thomas, 2007).

uncertainty in innovations in productivity and shopping quality.

Our framework controls for economies of scale and scope to capture that stores have become larger and offer a broader product variety. We allow investments in new technologies to improve productivity, which can sustain the observed increase in inventories over time and create incentives to increase product variety (Holmes, 2001).[4] For instance, bar codes and scanners have radically improved inventory management and the frequency of delivery. In addition, we allow adjustments in inventory and product variety to occur because managers target a better match with consumer preferences and consumers obtain quality from the shopping experience that includes accessibility and variety on the shelves.[5] In particular, we recover store productivity and shopping quality from a store's observed policies regarding labor and inventory demand accounting for investment in capital and technology, product variety, and the local environment in which the store operates.

We contribute to the extensive operations management literature that analyzes firm-level inventory behavior in retailing using aggregate inventory measures (e.g., Gaur et al., 2005; Rumyantsev and Netessine, 2007; Alan et al., 2014; Gaur et al., 2014; Cachon et al., 2018). Gaur et al. (2005) find that inventory turnover has a positive association with capital intensity and sales surprise and a negative association with gross margins. Inventory turnover is also positively correlated with store size, which can be explained by economies of scale and scope (Shockley and Turner, 2015). For instance, inventory turnover can increase due to economies of scale linked to the distribution network (Serpa and Krishnan, 2017).[6] Importantly, previous work emphasizes the need for future research on why heterogeneity in inventory turnover still remains even after controlling for firm characteristics (Gaur et al., 2005). Both demand and supply factors affect store markups and inventory productivity. There are open questions on how the trade-off between these factors explains differences in inventory behavior across stores. Using a complex multi-product sales technology, we complement this literature by providing a dynamic structural model that endogenizes inventory behavior at the store level and captures economies of scale and scope.[7]

A store must maintain a relatively large inventory to satisfy consumers when demand fluctuates, affecting the store's costs. In other words, the store's cost function depends on demand characteristics. In our model, this implies that the relationship between store productivity and shopping quality affects inventory behavior. Our model embodies primitives and their evolution, which are behind the heterogeneity in inventory performance and are also determinants of gross margins and capital intensity. Our analysis highlights the importance of various factors for inventory performance and product variety, such as (i) store total factor productivity and consumers' shopping quality; (ii) internal factors, i.e., investment and labor; and (iii) external factors, i.e., local market characteristics, such as population, income, and competition in local markets captured by rivals' productivity and shopping quality.

[4]We focus on investments in machinery and equipment and refer to this as investments in capital and technology. In retail, technology is embedded in machinery equipment (hardware), which is used to generate sales.

[5]Our measure of the quality of the shopping experience also includes features such as product quality, location, checkout speed, the courteousness of store employees, parking, bagging services, and cleanliness.

[6]The economies of scale and scope require that stores have excess capacity (supply chain infrastructure) such that stores can handle the volume of sales. In the absence of excess capacity, we have dis-economies of scale, which implies that inventory turnover and store size might be negatively correlated. Using a model with an exogenous productivity process, Serpa and Krishnan (2017) study the impact of supply chains on firm-level productivity and find that the effect of customers' productivity on the supplier's productivity is the primary source of spillovers (i.e., endogenous channel). They also find that it is more important for productivity to have a partner with high inventory turnover than to have one with high productivity (i.e., contextual channel).

[7]Unlike Serpa and Krishnan (2017), this paper does not focus on modeling vertical relations.

This paper also contributes to the recent literature that uses optimal decisions at the store/firm level to estimate productivity based on a sales or value-added production function (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Doraszelski and Jaumandreu, 2013; Ackerberg et al., 2015; Gandhi et al., 2018). First, we contribute to this literature by explicitly modeling the role of each product category for store-level sales and market share when recovering store productivity and consumers' perceived shopping quality. By applying our approach to rich data on products and stores, our work is linked to a recent avenue of research on multi-product firms in manufacturing (e.g., De Loecker et al., 2016; Dhyne et al., 2017) and in retail (Maican and Orth, 2018).[8] Store productivity and shopping quality affect the sales of the product categories. A store's market share contains information on how consumers choose stores in local markets that are used in the identification of shopping quality (Berry, 1994). Accounting for recent advances in technology that help to collect data about consumers, our model allows stores to learn from demand, that is, the quality of the shopping experience provides information that is used by stores to improve their future productivity. This mechanism of learning about demand has not yet received much attention in the structural productivity literature that endogenizes the productivity process.[9] Another contribution to the recent advances in productivity estimation is that we use inventory, the cost of goods sold, labor demand, investment, and product variety to recover two store-level unobservables (Kumar and Zhang, 2018; Maican and Orth, 2018).[10] The optimal inventory policy depends on the store's markups. While we do not observe prices, we can recover important determinants of marginal costs and prices, such as store productivity and shopping quality.[11] Lastly, this paper adds to the literature that explores heterogeneity in productivity in narrowly defined industries (Syverson, 2011) and to the scarce literature that estimates productivity in services industries (e.g., Basker, 2015; Maican and Orth, 2015; Maican and Orth, 2017; Serpa and Krishnan, 2017). The need to deal with consumers' shopping quality is particularly important in services because of difficulties in measuring physical quantities, implying that output is often measured by sales.

Our empirical results highlight that there are trade-offs between productivity and shopping quality that managers need to account for when deciding the optimal inventory, product variety, and inputs. Stores learn from consumers' perceived quality of shopping experience to increase future productivity. We find clear patterns for how the underlying theoretical primitives determine inventory turnover and the main trade-offs. Store productivity is a main determinant of inventory turnover. For example, a one percent increase in productivity increases inventory turnover almost two times more in the 75th productivity percentile than in the 25th percentile. Shopping quality

[8] De Loecker et al. (2016) and Dhyne et al. (2017) estimate productivity in manufacturing by accounting for multi-product and using the physical quantity; that is, they eliminate the impact of the average price on the productivity measure. In a companion paper on entry regulation, Maican and Orth (2018) present a general result on the identification of multi-output service generating functions that are used to recover total factor productivity and discuss the restrictions on the parameters that need to be satisfied for profit maximization.

[9] Recent literature emphasizes that external factors such as trade liberalization and entry regulations are important determinants of this heterogeneity (De Loecker, 2011; Maican and Orth, 2015; Maican and Orth, 2017). These explanations are added on top of factors inside the firm such as R&D investments (Doraszelski and Jaumandreu, 2013) or management (Syverson, 2011). Braguinsky et al. (2015) highlight the link between inventories, productivity and profitability.

[10] Kumar and Zhang (2018) also use the cost of goods to obtain information about demand in manufacturing in a setting that does not allow for product variety.

[11] Aguirregabiria (1999) models the interaction between price and inventory and its impact on markup dynamics and sales promotion using a complex dynamic model. Stock-outs create substitutability between prices and inventory in the profit function. In addition, the fixed ordering costs explain the coexistence of long periods of no price adjustments and short periods of very low prices.

also increases inventory turnover but at a substantially lower magnitude than productivity. Rivals' shopping quality in the local market is another important determinant of inventory turnover. Further, more intense competition from rivals' productivity increases inventory holdings with a larger magnitude in small markets than in large markets, which is consistent with the empirical findings of the scarce literature on competition and product variety (often used as a proxy for inventory) (e.g., Olivares and Cachon, 2009; Watson, 2009; Ren et al., 2011). Our findings also suggest that productivity drives the expansion of products in stores (Holmes, 2001). Furthermore, consumers in large markets and markets with large investments in technology benefit from a broader product variety.

The estimated model is used to simulate counterfactual policy experiments for a deeper understanding of the trade-off between store productivity and shopping quality. First, the simulation results show that productivity innovations play a crucial role in inventory behavior in the absence of changes in demand. For example, productivity improvements reduce the store's costs and increase the store's market power, which result in an increase in inventory at the end of the year and the number of product categories (Amihud and Mendelson, 1989).[12] Furthermore, inventory turnover grows more than the number of product categories. Second, the simulations show that the increase in inventory turnover is about three times larger after five years (7.3 versus 2.6 percent) if positive innovations in productivity are combined with a reduced uncertainty by 30 percent in shopping quality innovations than if they are not. The counterfactual simulations that stimulate shopping quality and lower uncertainty in productivity result in only a modest increase in inventory turnover. Stores substitute, however, labor for capital in the long run.

Our findings have direct managerial implications and can be used in the daily activities of retail managers to improve store performance. First, managers can ensure that inventory turnover climbs to high levels by actively becoming involved in activities that improve productivity and reduce uncertainty in consumers' shopping quality. Second, managers should also target productivity improvements because they are a key driver of product diversity inside the store. Third, demand and more intense competition in local markets will also be important for managers to monitor.

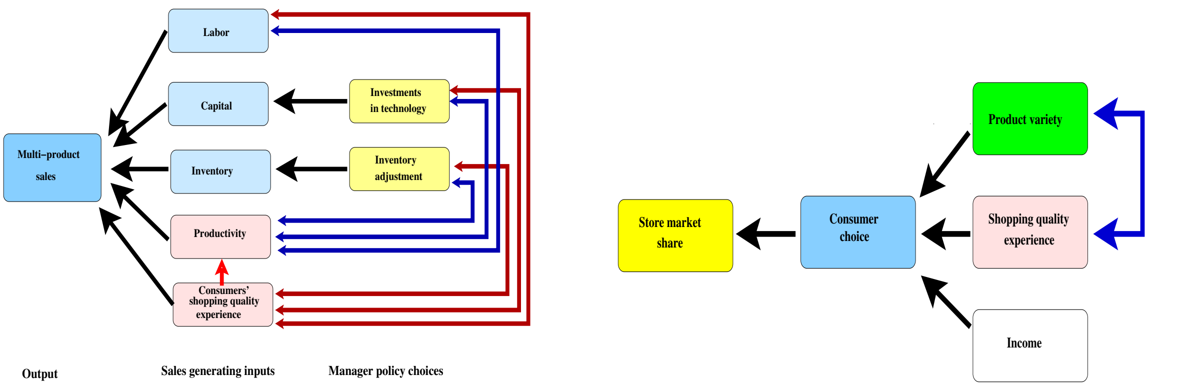
The next section presents the model and discusses the identification and estimation. Section 3 presents the data. Section 4 presents the empirical results. Section 5 shows the findings of various policy experiments using the estimated model. Section 6 presents robustness checks, and Section 7 summarizes and draws conclusions.

2 Empirical framework

This paper proposes a model for multi-product stores that endogenizes manager choices to study the relationship between store total factor productivity and shopping quality and the observed heterogeneity in inventory and product variety in retail. The proposed model underlines the factors behind the trend of increasing inventories in different retail industries, which is consistent with the development toward larger stores that offer more product categories, i.e., the utilization of economies of scale and scope.

We use a multi-product sales generating function together with a demand system to estimate

[12] Amihud and Mendelson (1989) find a positive relationship between market power and inventory level and variability. Using cross-industry data, Scherer and Ross (1990) find a positive correlation between the concentration ratio and inventory variability.



Panel A: Multi-product sales Panel B: Consumer choice and store market share

Figure 1: Model description

a store's total factor productivity and demand shocks related to consumers' quality of the shopping experience that affect store choices, such as labor and products bought from the wholesaler, investment in technology, and the number of products. Figure 1 shows a simple description of our model and presents the channels that affect manager choices and store performance (sales, market share, and inventory turnover). Panel A in Figure 1 shows the relationships between the determinants of sales in multi-product stores. Managers decide labor, investment, the number of products, and inventory adjustments based on productivity and shopping quality to generate sales. The two-way arrows point to endogeneity concerns caused by correlations between the decision variables by managers and the store-level shocks in productivity and shopping quality. Panel B shows factors that consumers take into account when choosing a store, i.e., product variety, shopping quality and income, which in turn determine the store's market share.[13]

In our model, differences in inventories and inventory performance across stores can arise because of differences in (i) productivity; (ii) quality of the shopping experience; (iii) internal factors such as stock of capital/technology inside the store; and (iv) external factors, i.e., local market characteristics.[14] To improve inventory management, stores invest in technology which increases productivity and reduces the cost of inventories. The proposed model focuses mainly on understanding the relationship between store-level inventory and performance, productivity, quality of the shopping experience and omits explicitly modeling stock-outs, depreciation, and fixed costs.

Multi-product service generating function. In our setting, stores use the same service technology to sell their products, and this technology does not depend on the product category. Stores compete in the product market and collect their payoffs. At the beginning of each time period, stores decide whether to exit or to continue to operate in the local market. Stores are assumed to know their scrap value received upon exit prior to making exit and investment decisions. If a store continues, it chooses optimal levels of the number of products, products bought from the wholesaler and the adjustments in inventory before sales a, investment in capital/technology i,

[13]While prices also affect the choice of store, they might be difficult to access for rich census data on retail stores due to different pack sizes, units of measure, etc. However, the empirical literature on total factor productivity estimation shows how to deal with unobserved prices and discusses the limitations (Klette and Griliches, 1996; De Loecker, 2011).

[14]Lower markups decrease inventories, whereas a large choice set for consumers increases inventories (Cachon and Olivares, 2010).

and labor l (the number of employees).[15]

The service generating function for a multi-product store j can be described by a transcedental function that generalizes Cobb-Douglas (Mundlak, 1964; Maican and Orth, 2018), i.e.,[16]

$$\sum_{i=1}^{d} \tilde{\alpha}_i q_{ijt} + \tilde{\alpha}_y Y_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\beta}_a a_{jt} + \tilde{\omega}_{jt} + \tilde{u}^p_{jt}, \tag{1}$$

where q_{ijt} is the log of quantity of product i sold by store j in period t; Y_{jt} are total sales of store j in period t; l_{jt} is log of the number employees; k_{jt} is log of capital stock;[17] a_{jt} is log of the sum between the inventory level in the beginning of period t (n_{jt}) and the products bought during period t; $\tilde{\omega}_{jt}$ is quantity based total factor productivity (TFP, technical productivity); and $\tilde{u}^p_{jt}$ are i.i.d. remaining service output shocks.[18] Inventories enter as an input of the service generating function since the core activity of retail stores is to buy finished products from wholesalers and resell them to consumers.[19] Moreover, decisions about inventories are strategic and dynamic, i.e., affect long-run profits. A store's optimal inventory level balances two counteracting forces. Inventories reduce the risk of stock-outs and increase shopping quality but are costly to adjust and hold in stock. Inventories provide a convenience yield to consumers because they reflect the reduction in shopping cost, i.e., less frequent stock-outs, provision of variety, and other benefits associated with the underlying retail services (Working, 1949; Brennan, 1958; Pindyck, 1994; Cachon et al., 2018).

Product demand. We assume that consumers are homogeneous and have CES preferences over differentiated products and services $i \in \{1, \cdots, d\}$ inside the store. We exploit the link between a CES demand system and a discrete choice demand system, which allow us to write the consumer choice probability equation from the CES preferences (Anderson et al., 1987; Anderson and De Palma, 2006; Hortacsu and Joonhwi, 2015). Using this relationship, the log of the price of product i (p_{ijt}) from the consumer choice probability equation is given by

$$p_{ijt} = -\frac{1}{\sigma}(q_{ijt} - q_{0t}) + \mathbf{x}'_{ijt}\frac{\boldsymbol{\beta}_x}{\sigma} + \frac{\sigma_a}{\sigma} a_{jt} + \frac{1}{\sigma}\tilde{\mu}_{ijt}, \tag{2}$$

where $\mathbf{x}_{ijt}$ are the observed determinants of the intensive and extensive margins of the utility function when consumers buy the product i; σ is the elasticity of substitution; $\tilde{\mu}_{ijt}$ are unobserved product characteristics for the econometrician, e.g., unobserved quality of shopping experience for product i in store j in period t; and q_{0t} is the outside option.[20] The presence of a_{jt} in equation (2) captures that consumers prefer in stock products to minimize the search cost. The vector $\mathbf{x}_{ijt}$

[15] We follow the common notation of capital letters for levels and small letters for logs.

[16] In a companion paper, Maican and Orth (2018) present a general result on the identification of multi-output service generating functions following Mundlak (1964) and discuss the restrictions of the parameters that are need to be satisfied for profit maximization.

[17] Capital stock is a dynamic input that accumulates according to $K_{jt+1} = (1-\delta)K_{jt} + I_{jt}$, where δ is the depreciation rate. The investment I_{jt} in machinery and equipment is chosen in period t and affects the store in period $t+1$.

[18] We can write a total sales generating function using Cobb-Douglas technology (in logs) at the store level instead of at the product level, i.e., no product information, $y_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\beta}_a a_{jt} + \tilde{\omega}_{jt} + \tilde{\mu}_{jt} + u_{jt}$, where $\tilde{\mu}_{jt}$ are correlated demand shocks that include the quality of the shopping experience. Maican and Orth (2018) use a simple demand and supply model to show the intuition behind the derivation of this aggregate service function equation.

[19] Recent literature on inventory explains the differences and the role of input and output inventories, e.g., Humphreys et al. (2001), Iacoviello et al. (2011), and Wen (2011).

[20] Equation (2) is similar to the logit discrete choice demand system, but the price is in logs.

includes observed product and store characteristics and local market characteristics (for example, population, population density, and income). To simplify the notation, we omit the local market index m when the store index j is present and we refer to store j in market m.

We can use the service production (1) and the price equation (2) to obtain the sales generating function at the store level, i.e., $y_{ijt} = q_{ijt} + p_{ijt}$ (see Maican and Orth, 2018):

$$y_{ijt} = -\alpha_y y_{-ijt} + (\beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt}) + \beta_q y_{0t} + \mathbf{x}'_{jt}\boldsymbol{\beta}_x + \omega_{jt} + \mu_{jt} + u^p_{ijt}, \tag{3}$$

where y_{ijt} is the log of the sales of product i in store j in market m in period t; y_{-ijt} is the log of the sales of products other than product i in store j; y_{0t} measures sales of the outside option captured by the sales of products in a local market m that do not belong to the five-digit sub-sector of product i; ω_{jt} is the multi-factor sales productivity (TFPR), which we refer to as productivity; and u^p_{ijt} are i.i.d. remaining shocks to sales that are mean independent of all the control variables and store inputs. The vector $\mathbf{x}_{jt}$ sums all observed characteristics at the store and market levels. The variable μ_{jt} sums all remaining unobserved product characteristics at the store level that affect consumer choices (i.e., demand shocks). These demand shocks μ_{jt} are correlated with inventories and sales.[21] We refer to demand shocks μ_{jt} as a measure of customer satisfaction and the quality of the shopping experience in store j in period t. Productivity ω_{jt} and demand shocks μ_{jt} are unobserved by the researcher, but they are known by the stores when making decisions. The new parameters of the multi-product sales generating function (3) are re-scaled using σ and $\tilde{\alpha}_y$ ($\beta_q = 1/\sigma$), i.e., they depend on the elasticity of substitution and competition between product categories inside the store.

Consumers' choice of store. Because the demand shocks μ_{jt} contain information about the quality of the shopping experience in a store, they affect consumers' store choice. Therefore, we can recover information about them from an aggregate discrete choice demand system at the store level, where the consumer's utility of choosing store j depends on the number of products (categories) np_{jt}, the log of average income in the local market inc_{mt}, and quality of the shopping experience μ_{jt}. Assuming i.i.d. Type-1 extreme value shocks on the preferences for stores, we obtain the market share equation (see Berry, 1994)

$$ln(ms_{jt}) - ln(ms_{0t}) = \rho_{np} np_{jt} + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc^2_{mt} + \mu_{jt} + \nu_{jt}, \tag{4}$$

where ms_{jt} is market share of store j in local market m in period t computed at the five-digit industry level; ms_{0t} is the outside option, i.e., the market share of other stores in market m; and ν_{jt} is mean independent of all the controls.

Sales are a commonly used output measure in services and depend on both demand and supply factors. In our model, sales depend on both the quality of the shopping experience μ_{jt} and productivity ω_{jt}, whereas a store's market share depends only on μ_{jt}. In other words, the market share equation (4) and the sales generating function (3) are linked through the quality of the shopping experience μ_{jt}. It is important to note that the shopping quality μ_{jt} measures factors other than product variety and demand shifters. Furthermore because the sales generating function (3) controls for capital stock k_{jt} and inventory a_{jt}, they are not part of μ_{jt}, and we do not need to control for them in the market share equation.[22] The number of products (categories) np_{jt} is

[21] Even if we control for demand shocks μ_{jt}, there may still be other shocks remaining in productivity ω_{jt} when the current explanatory variables do not capture demand heterogeneity.

[22] Even if we control for capital stock k_{jt} and inventory a_{jt} in the market share equation, we cannot separately identify their effects on demand and supply (Ackerberg et al., 2007). That is, we will not be

part of a_{jt}, but a_{jt} includes additional information, such as the volume of each product, and the products are aggregated based on monetary value.

Adjustment in inventory. We model inventory as a type of capital that evolves endogenously based on products bought from the wholesaler and adjustments in inventory, and it is characterized by adjustment and holding costs. The evolution and adjustments in inventory follow previous literature (e.g., Coen-Pirani, 2004). Inventory level at the beginning of period $t+1$ evolves according to $N_{jt+1} = A_{jt} - Y_{jt}$, where A_{jt} is the adjusted inventory before sales, i.e., the inventory in the beginning of the period N_{jt} adjusted with the products bought in period t, and Y_{jt} is store-level sales. That is, N_{t+1} captures inventory in the beginning of period $t+1$ (or end of period t) after sales in period t are realized.

We build on previous work that emphasizes a link between inventory, demand, supply, productivity, and sales over time (Kesavan et al., 2011; Kesavan and Mani, 2013; Alan et al., 2014; Cachon et al., 2018). Inventories affect store service output because high inventories are costly to keep in stock and low inventories reduce consumers' choices. There is a distinction between how μ_{jt} affects current inventories and products bought from the wholesaler, on one hand, and the realization of inventories in the end of the year/start of next year on the other. A high quality of the shopping experience μ_{jt} makes stores increase their products bought from wholesalers. However, it might also lead to a drop in inventories at the beginning of the following year because of an unexpected increase in sales.

Stores trade-off consumer quality and the risk of stock-outs against holding costs when deciding optimal inventory levels. Recent investments in new technologies in retail, such as bar codes and scanners, have drastically reduced information distortion, lead-time, uncertainty, and errors. For instance, stores can use real-time information about product flows to improve predictions of and adjustments to demand and to strengthen the supply chain management, which implies that technological advancements increase the frequency of turnover and lower inventories. New technologies also create possibilities for the store to provide a wider variety of products and services at a lower cost. Lower holding costs for inventories increase the incentives to keep products in stock in order to guarantee consumer choices and high quality and to avoid stock-outs.

Evolution of productivity and shopping quality. Both store productivity ω_{jt} and the quality of the shopping experience μ_{jt} are correlated over time, and they are not observed by the researcher. Inventory holdings and investments in technology both have dynamic implications due to adjustment costs, and both ω_{jt} and μ_{jt} are important for such adjustments. We thus need to specify how the productivity and demand shocks evolve over time. The quality of the shopping experience shocks μ_{jt} are correlated over time according to the following nonlinear AR(1) process

$$\mu_{jt} = \gamma_0^\mu + \gamma_1^\mu \mu_{jt-1} + \gamma_2^\mu (\mu_{jt-1})^2 + \gamma_3^\mu (\mu_{jt-1})^3 + \eta_{jt}. \tag{5}$$

Store productivity ω_{jt} follows an endogenous nonlinear AR(1) process where previous productivity ω_{jt-1} and the quality of the shopping experience μ_{jt-1} affect current productivity

$$\begin{aligned} \omega_{jt} = \; & \gamma_0^\omega + \gamma_1^\omega \omega_{jt-1} + \gamma_2^\omega (\omega_{jt-1})^2 + \gamma_3^\omega (\omega_{jt-1})^3 + \gamma_4^\omega \mu_{jt-1} \\ & + \gamma_5^\omega \omega_{jt-1} \times \mu_{jt-1} + \xi_{jt}. \end{aligned} \tag{6}$$

η_{jt} and ξ_{jt} are shocks to demand and productivity, respectively, which are mean-independent of all information known at $t-1$.

Our model allows store productivity to be influenced by the quality of the shopping experience that affects consumers' store choice and the market shares. The demand shocks associated with

able to separately identify the effect of inventory on supply and demand, i.e., we identify the net effect.

the quality of the shopping experience can influence store productivity in at least two ways. The first is through productivity gains within stores that arise, for instance, because stores obtain opportunities to analyze information from consumers and use it to improve the shopping process and inventory management. For example, store employees are responsible for many small improvements to shopping quality. The second channel is through a selection effect from the exit of low-productivity stores. Productivity changes as a result of changes in the quality of the shopping experience, although we also recognize that it is plausible that stores engage in other active efforts to increase their productivity. Our model quantifies the overall effect of the quality of the shopping experience on productivity rather than modeling all the possible sources of productivity improvement.

Manager's optimal choices. Stores know their productivity ω_{jt} and the quality of the shopping experience μ_{jt} when they make their input and exit decisions. The model therefore yields managers' optimal choices, that is, the policy functions for inventory, investments, and labor, along with the number of products, as nonparametric functions of the store's state variables. That is, the optimal inventory is $a_{jt} = f_t(\omega_{jt},\ \mu_{jt},\ k_{jt},\ n_{jt},\ \mathbf{x}_{jt})$, investment is $i_{jt} = i_t(\omega_{jt},\ \mu_{jt},\ k_{jt},\ n_{jt},\ \mathbf{x}_{jt})$, labor is $l_{jt} = l_t(\omega_{jt},\ \mu_{jt},\ k_{jt},\ n_{jt},\ \mathbf{x}_{jt})$, and number of products is $np_{jt} = np_t(\omega_{jt},\ \mu_{jt},\ k_{jt},\ n_{jt},\ \mathbf{x}_{jt})$. The policy functions capture complex decisions by managers, where current choices affect the future development of the store. The estimation of policy functions is crucial for our empirical analysis and counterfactual simulations on how productivity and shopping quality influence inventory, investment, the number of employees, and the number of products (Bajari et al., 2007; Ackerberg et al., 2007).

Endogenous inventory productivity. To measure inventory performance, various measures have been used in the literature, such as inventory turnover, defined as cost of products sold over inventory, the sales-to-inventory ratio, and gross margin to inventory. In the empirical implementation, we focus mainly on the inventory turnover measure, defined as the cost of products sold divided by average store-level inventory in period t and $t+1$ (see Section 3).[23] These variables that define the ratio are outcomes (solutions) of the manager's dynamic optimization problem. Therefore, they are functions of state variables, which makes inventory performance a function of the state variables. In other words, our model pins down theoretical determinants of inventory performance that are consistent with the manager's optimal decisions in the short and long run, i.e., $it_{jt} = it_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, \mathbf{x}_{jt})$. The suggested framework complements the existing work on inventory turnover and adjusted inventory turnover (e.g., Gaur et al., 2005; Cachon et al., 2018). In the empirical implementation, we estimate the evolution of the inventory performance function $it_{jt}(\cdot)$ (inventory turnover), which allows us to evaluate how inventory productivity changes when a store's primitives change due to various policy changes.

The state variables ω_{jt} and μ_{jt} follow two dynamic processes, and their characteristics affect the inventory behavior. For example, by understanding the persistence in store productivity, managers obtain information about the persistence in inventory productivity and the effect of changes in inputs and investments. To provide intuition for this argument, we discuss a simplified version of our model and assume that ω_{jt} and μ_{jt} follow simple AR(1) processes, e.g., $\omega_{jt} = \rho\omega_{jt-1} + \xi_{jt}$, where ρ is a coefficient capturing the persistence in store productivity and ξ_{jt} is i.i.d. innovation shocks to productivity. Moreover, considering aggregate sales and defining the log of the sales-to-inventory ratio in period t after the realization of sales as $it_{jt} = y_{jt} - n_{jt+1}$, a dynamic equation for the inventory productivity (i.e., process) can be derived using the production tech-

[23] Alternative measures such as the sales-to-inventory ratio and the adjusted inventory turnover ratio are discussed in the robustness and the online Appendix.

nology: $it_{jt} = \rho it_{jt-1} + \lambda(\cdot)$, where $\lambda(\cdot)$ is a function of first differences in l_{jt}, k_{jt}, a_{jt}, n_{jt+1}, μ_{jt}, u_{jt}, and ξ_{jt} (see online Appendix A).[24] In other words, the persistence of the store productivity process ρ drives the persistence of the inventory productivity process. Recent studies on retail find an average persistence in store productivity of approximately 70-80 percent (Maican and Orth, 2017).

The relationship between the processes of productivity, shopping quality and inventory performance have several important implications for managers. First, the innovation shocks in store productivity ξ_{jt}, shopping quality η_{jt}, and sales u_{jt} affect inventory performance. This phenomenon is important since innovation shocks ξ_{jt} and η_{jt} provide information about uncertainty in store productivity and shopping quality and affect optimal inventory and input choices (labor and capital). In addition, their effects accumulate over time. Therefore, managers can learn how uncertainty in a store's total factor productivity affects inventory performance by understanding the distribution of ξ_{jt}. If the innovation shocks ξ_{jt} have large variance, managers must prevent negative consequences of large variance in inventory performance by implementing policies to increase the persistence in store productivity (for example, investments in technology, optimal labor-capital substitution, and the optimal choice of product variety). Second, adjustments in inventory and input choices over time directly influence inventory performance because optimal changes in labor and capital affect store productivity and, therefore, inventory performance. Most importantly, our suggested framework and empirical implementation account for heterogeneity in stores' responses to productivity and shopping quality changes, that is, we allow for nonlinear processes.[25]

Identification and estimation. The identification and estimation of the sales generating function (3) follows the Olley and Pakes (1996) literature and Maican and Orth (2018), which include the estimation of the Markov processes for ω_{jt} and μ_{jt}. We estimate θ=(β_l, β_k, β_a, β_x, α_y, β_q, ρ_{np}, $\rho_{inc,1}$, $\rho_{inc,2}$) using a two-step estimator and the store's labor demand function to recover productivity (Doraszelski and Jaumandreu, 2013; Maican and Orth, 2017).[26] In contract to Olley and Pakes (1996) literature, we have two unobservables to recover instead of one (see also Maican and Orth, 2018). We use the store's demand for inventory a_{jt} to recover the quality of the shopping experience μ_{jt}. The online Appendix B provides additional details on the estimation and identification.

Because productivity ω_{jt} and μ_{jt} are functions of coefficients of the service generating function and market shares, we can identify θ coefficients using moment conditions based on $(\xi_{jt} + u_{ijt})$ and $(\eta_{jt} + \nu_{jt})$ and the generalized method of moments (GMM) estimator. In fact, we can identify $\tilde{\beta}_l$, $\tilde{\beta}_k$, and $\tilde{\beta}_a$, $\tilde{\beta}_q$, $\tilde{\beta}_x$ up to a scale. To allow for comparisons across specifications, the two-step estimated coefficients are adjusted for elasticity of substitution σ and the coefficient of other product categories inside the store $\tilde{\alpha}_y$.

To identify θ the following moment conditions are used, i.e., $E[\xi_{jt} + u_{ijt}|\ y_{-ijt-1}, l_{jt-1}, k_{jt-1}, a_{jt-1}, \mathbf{x}_{mt-1}] = 0$ and $E[\eta_{jt} + \nu_{jt}|np_{jt-1}, inc_{mt-1}, inc^2_{jt-1}] = 0$. That is, we use that the remaining shocks are not correlated with the previous variables to form the moments.[27] It is important to note that having the parameters of the multi-product sales generating function and the market share equation, we estimate the parameters of the Markov processes. The parameters $\boldsymbol{\theta}$ are

[24] n_{jt+1} is inventory at the beginning of period $t + 1$ (end of period t) after sales are realized.

[25] Nonlinearities in store productivity complicate the dynamics of inventory performance compared to a simple AR(1) process (Ackerberg et al., 2007).

[26] Levinsohn and Petrin (2003) use intermediate inputs to recover productivity.

[27] Ackerberg et al. (2007) and Wooldridge (2009) provide an extensive discussion on using previous variables as instruments in a twp-step control function approach when estimating production functions.

estimated by minimizing the GMM objective function

$$\min_{\boldsymbol{\theta}} Q_N = \left[\frac{1}{N} W' v(\boldsymbol{\theta})\right]' A \left[\frac{1}{N} W' v(\boldsymbol{\theta})\right], \tag{7}$$

where $v_{jt} = (\xi_{jt} + u_{ijt}, \eta_{jt} + \nu_{jt})'$, W is the matrix of instruments, A is the weighting matrix defined as $A = \left[\frac{1}{N} W' v(\boldsymbol{\theta}) v'(\boldsymbol{\theta}) W\right]^{-1}$.[28]

3 Data description

The empirical application focuses on the three-digit industry *Retail sale of new goods in specialized stores* (Swedish National Industry (SNI) code 524). This retail sector includes the following sub-sectors at the five-digit SNI: clothing; footwear and leather goods; furniture and lighting equipment; electrical household appliances and radio and television goods; hardware, paints and glass; books, newspapers and stationery; and specialized stores.

We use two data sets provided by Statistics Sweden. The first data set covers detailed annual information about all retail firms in Sweden (census) from 2000 to 2009. The data contain financial statistics of input and output measures, i.e., sales, value-added, number of employees, capital stock, inventories, cost of products, and investment. Inventories capture the value of products held in stock by the end of each year and are taken from book values (accounting data). Sales are measured in output prices, whereas the cost of products and inventories are measured in input prices (what stores pay to the wholesaler). Because of difficulties in measuring quantity units in retailing (and services) arising from the nature and complexity of the product assortments, quantity measures of output and inventories are not available in many data sets (for example, census data). In retail, we often refer to firms as stores. In our data, a unit of observation is an organization number.[29] We observe the municipality in which each organization number is physically located. Therefore, an advantage of our data is that we can exploit the local variation and study the impact of competition.

Our second data set covers store-level information on the number of products (product categories) and their values sold each year. To the best of our knowledge, such detailed data on the number of products across stores and local markets in services industries have not previously been used in the literature. The data cover all product categories that a store sells on a yearly basis. Unique identification codes allow us to match products perfectly to stores.[30] To reduce the dimensionality of the product space in the empirical application, we use well-defined product categories to define store products, for example, shoes for women, shoes for men, and shoes for children. Most importantly, the combination of the two data sets allows us to compute product market shares inside a store and a store's market share in a geographic market, which provides rich information related to competition. Furthermore, the mix of product-level and store-level data is novel and, to the best of our knowledge, has not been used in service industries before.

[28] Standard errors are computed according to Ackerberg et al. (2012). Bootstrapping might not be the best choice when the underlying model is more complicated.

[29] In a few cases in our data, an organization number can consist of more than one physical store (a multi-store) in the same municipality, for which we observe total, not average, inputs and outputs. Multi-store reporting is less than 5 percent in our sample (Maican and Orth, 2015).

[30] The product data set follows a similar classification system to the one used for the sample data collected on prices and quantities in manufacturing (PRODCOM).

Inventory performance measures. We apply commonly used measures of inventory productivity by managers and analysts to evaluate inventory performance of the store. Inventory turnover measures the number of times inventory turns. First, we define inventory turnover as the cost of goods sold over average inventory. Second, we use inventory turnover defined as sales over inventory.[31] Third, we use an adjusted inventory turnover measure that is computed as in Gaur et al. (2005) using the determinants of inventory performance, such as the gross margin and capital intensity.

Descriptive statistics and stylized facts. Figure 2 shows that there is a strong positive trend in inventories, investments in new technology and inventory turnover (the sales-to-inventory ratio) using aggregate data at the retail industry level. The positive co-movement between inventory and inventory turnover is consistent with the view of inventory as a convenience yield that helps to avoid stock-outs. In addition, the positive co-movement between inventory and investment in technology suggests that there are common factors that affect these variables. In particular, we exploit that stores make endogenous input choices of both investments and inventories, and the implications for productivity.

Table 1 shows that there is an aggregate increase in investments, inventory, labor, value-added, sales and the average number of product categories over time. From 2005 to 2009, sales increased by 36 percent, inventory by approximately 30 percent, investments by 53 percent and the number of employees by 21 percent. Inventories more closely follow the business cycle, e.g., the highest value in 2007 was followed by a 20 percent drop in 2008, when the economic crisis started. However, the highest investment occurred in 2008, which suggests that stores invested in technology to increase their productivity and to reduce the cost of inventories to compensate for negative shocks in demand. An average store has about 4 product categories, and the number of product categories varies between 1 and 17 in our sample.

The scatter plots in Figure 3 are the first step to study the basic relationships (no causation) between inventory turnover and the number of product categories on one hand and labor productivity and investment in technology (machinery and equipment) on the other. Simple linear and nonlinear regressions indicate that there is a positive relationship between labor productivity and inventory turnover (Lieberman and Demeester, 1999).[32] On average, stores with high labor productivity have high inventory turnover and large product variety. In addition, the scatter plots also show that stores with large investments have high inventory turnover and large product variety. Because all the variables in Figure 3 are endogenous, we need to estimate the model presented in Section 2 to understand what drives these correlations.

4 Results

This section presents the empirical results. First, we discuss the results of the estimated multi-product sales generating function, including estimates of store productivity and customers' perceived quality of the shopping experience and how they evolve over time.[33] Second, we examine

[31] The average inventory between period t and $t+1$ is often used. Based on annual data, we can also construct the number of days inventory is at hand, for example, $365/(sales_{jt}/inventory_{jt})$.

[32] Using manufacturing data from the Japanese automotive industry, Lieberman and Demeester (1999) find a negative correlation between the inventory-to-sales ratio (i.e., the inverse of inventory turnover) and labor productivity.

[33] To allow for comparisons across specifications, we show the results using the two-step estimator where coefficients are adjusted for the elasticity of substitution σ and the coefficient of other product categories

the determinants of managers' optimal choices of inventory, investment, labor and the number of product categories, which are functions of the state variables. Third, we study the determinants of inventory turnover and begin by presenting the results following the existing approaches to our data (Gaur et al., 2005). Then, we extend the analysis by including store productivity and shopping quality and allowing the empirical specification of inventory turnover to be consistent with the store's short- and long-run profit maximization. Our results explore the heterogeneity in productivity and shopping quality and their role in explaining inventory dynamics and performance across retail stores. Readers interested only in the primary results related to inventory turnover and counterfactual simulations can proceed directly to Section 4.2.

Service generating function estimates. Table 2 shows the estimates of the multi-product service generating function (equation (3)) by the ordinary least squares (OLS) estimator and the nonparametric two-step estimator presented in Section 2. The two-step estimator controls for the endogeneity of store input choices (i.e., simultaneity) and allows us to identify store productivity separately from shocks to market share. By using the two-step estimator, the coefficients of labor and inventories decrease from 0.786 (OLS) to 0.539 and from 1.036 (OLS) to 0.439, respectively. The coefficient of capital increases from 0.059 (OLS) to 0.227 (the two-step estimator). These changes in the estimates are in line with the production function literature following Olley and Pakes (1996), which suggests that there exists an upper bias for the coefficients of labor and inventories when omitting to control for the correlation between inputs and productivity.

The estimated elasticity of demand for product substitution ($1/\sigma$) is 4.59. There is clear evidence of competition for limited shelf space among products in a store. Sales of a product category decrease in sales of other product categories. With the same resources, a 1 percent increase in sales of a product category decreases sales of other product categories by 0.865 percent. This finding is consistent with profit maximization behavior of multi-product firms (Mundlak, 1964; Maican and Orth, 2018). The coefficient of a store's other product categories influences the input coefficients, which affect the productivity measure. The findings also show that stores in markets with high population density sell more in each product category (i.e., demand effect).

The results from the market share equation (4) clearly show that a store's market share increases in product variety (0.217). In other words, a wider span of products increases the market share.[34] Income has a positive effect on the consumer's utility function and, therefore, on a store's market share.

Productivity and consumers' perceived quality. The heterogeneity of productivity and shopping quality is informative for store managers because it drives the heterogeneity in sales across stores. Using the estimated parameters from the sales generating function, we recover productivity ω_{jt} and shopping quality μ_{jt} for each store and year. Store shopping quality μ_{jt} has a larger variance than productivity ω_{jt}. For productivity, a store in the 75th percentile has 27 percent greater productivity than a store in the 25th percentile. However, the shopping quality is approximately 50 percent higher for a store in the 75th percentile than for a store in the 25th percentile.

Table 3 shows the estimates of the processes for store productivity ω_{jt} and shopping quality μ_{jt}, i.e., equations (6) and (5). The persistence of the productivity process (0.871) is lower than the persistence of the shopping quality (0.941). The magnitude of the persistence in productivity is similar to the findings in other studies in the productivity literature (e.g., Doraszelski and Jau-

inside the store $\tilde{\alpha}_y$.

[34]For example, a store with a 30 percent market share in a local market increases its market share to 35 percent by adding one more product category.

mandreu, 2013 – manufacturing; Maican and Orth, 2017 – retail).

In our model, shopping quality can affect store productivity, and the size of the impact depends on the level of store productivity. The results in Table 3 show that we reject the null hypothesis that the coefficients of shopping quality μ_{jt} in the productivity process are equal to zero (*p-value*=0.000). The shopping quality has a positive impact on productivity, i.e., a one percent increase in μ_{jt} raises productivity by 0.018 percent on average. This finding suggests that stores use information from consumers' choice to improve productivity, that is, learning from managing demand. For example, consumers assign high shopping quality to stores with skilled and service-minded employees who help them during the shopping process. These high-ability employees use information from consumers to create appealing innovations that shift store productivity.

4.1 Managers' optimal decisions

Table 4 shows the estimates of the policy functions for inventories, product variety, investments in technology and labor demand as functions of the state variables. We explore two measures of inventory: first, inventory before sales are realized (a_{jt}), that is, inventory at the beginning of period t plus products bought; and second, inventory at the end of period t after sales are realized (i.e., (n_{jt+1}) inventory in the beginning of period $t+1$). The state variables that are used to decide optimal choices are productivity (ω_{jt}), shopping quality (μ_{jt}), previous capital and investment (k_{jt-1}, i_{jt-1}), inventories at the beginning of the period (n_{jt}), and local market characteristics ($\mathbf{x}_{jt}$). The optimal choices are nonlinear functions, and we allow them to depend on current levels of productivity and shopping quality in a flexible way. T-tests reject the hypotheses of zero coefficients of the productivity and shopping quality. In the text, we focus on marginal effects evaluated at the median values.[35]

Inventory behavior. First, the state variables explain approximately 95 percent of the variation in the level of inventory (before and after the realization of sales). Stores with high productivity and shopping quality have high inventories a_{jt}, but their marginal effects on inventories decrease with the magnitude of these measures. Inventory increases substantially more from shopping quality than from productivity shocks. For the median store, a 3.7 percent increase in inventory before sales (a_{jt}) is the optimal response to a 10 percent increase in store productivity. The corresponding increase in inventory from a 10 percent increase in shopping quality is 8.7 percent, i.e., more than double that of productivity. A stronger effect of shopping quality than of productivity reflects that the inventory measure a_{jt} includes products bought, and consumers' perceived shopping experience plays a key role when deciding the optimal adjustment in inventory.

For the end of year inventory (after sales are realized), the effect of an increase in productivity is higher than that of an increase in shopping quality. A 10 percent increase in productivity increases end of year inventory by 15 percent. The corresponding increase from shopping quality is 8 percent, i.e., half of the productivity effect. Store productivity thus plays a more important role than demand shocks for the end of the year inventory after sales are realized.[36] As expected, stores that have large investments and capital stock, and that are located in large markets or

[35]Our results remain robust using a full polynomial expansion of order 2 and 3. The marginal effects are functions of the estimated coefficients in Table 4.

[36]Because higher productivity and shopping quality increase a store's market power, these findings are consistent with Amihud and Mendelson (1989), who show that firms with greater market power hold more inventories and have higher volatility in inventories.

markets with high population density have higher inventories.

A managerial implication is thus that managers need to keep track of that optimal inventory before sales reacts more strongly to changes in shopping quality and optimal inventory after sales reacts more strongly to productivity shocks.

Product variety. Table 5 shows estimates of the number of product categories in a store as a function of the state variables. We also use a Herfindahl index (HHI) calculated based on sales of product categories inside the store and the number of unique product categories in local markets as the dependent variable.

Improving productivity allows stores to increase the number of product categories, although the magnitude of the increase declines toward the upper tail of the productivity distribution. A broader product assortment is thus driven by productivity. Stores with high shopping quality differentiate more by offering a larger number of products, as indicated by the linear marginal effect. In contrast, stores with a low shopping quality decrease their number of product categories, i.e., it is optimal for them to specialize. Large stores and stores that invest in new technology have, as expected, more product categories. The results for the HHI yield consistent results, i.e., that higher productivity and investments are associated with a lower concentration of products. That is, productivity improvements and investments increase "sales competition" between product categories inside the store.

Finally, the estimates for the number of unique products in a market show that consumers in large local markets with stores that invest in technology benefit from a larger product variety. A positive relationship between market size and product variety is consistent with findings in recent work (for example, Berry and Waldfogel, 2010; Berry et al., 2016).

Investment and labor demand. Stores with high productivity and shopping quality invest more in technology, consistent with the store's dynamic programming problem and in line with previous work based on the Olley and Pakes' framework, where optimal investment demand increases with productivity.[37]

A 10 percent increase in productivity increases the demand for investment by 6.3 percent for the median-productivity store. Shopping quality increases the store's optimal investments, but at a decreasing rate. A 10 percent increase in shopping quality increases investments by 1 percent. For example, a store with low productivity that receives a large shock in shopping quality invests in new technology to improve productivity, to avoid stock-outs and to enhance its inventory management. These findings are consistent with the positively correlated trends of inventories and investments in new technology in Figure 2. A low persistence in investments indicates that productivity and shopping quality play a key role in optimal investment choices. Higher capital stock and beginning of the year inventories also have a positive and statistically significant effect on store investment, which can be associated with the size effect, i.e., large stores have high investments.

The consumer shopping experience also depends on the employees inside the store. We find that the number of employees is increasing in productivity and shopping quality. Furthermore, stores in large and densely populated markets have more employees.

Managerial implications. For managers, our estimates of optimal decisions suggest that productivity improvements bring an increase in the flow of products to consumers and allow stores to manage a wider product variety. Productivity as a main driver of product variety links closely

[37] In this paper, investments in machinery and equipment are associated with investments in technology. For example, a new refrigerator includes innovations in both design and technology, which saves space and costs and allows more products to be exposed efficiently.

to the work by Holmes (2001). At the same time, stores hold more inventories to avoid declining sales due to stock-outs (e.g., consumers might switch to other stores). Managers' optimal choice of products also depends on whether the store currently offers a high- or low-quality shopping experience. That is, high-quality stores can handle wider product variety, whereas low-quality stores need to specialize in selling fewer products. We conclude that there are complex trade-offs between productivity and shopping quality that are important for managers to account for when deciding the optimal product mix in the store.

4.2 Inventory turnover

A key advantage of our model is that it endogenizes inventory turnover, where the determinants of inventory turnover are theoretically consistent with the store's dynamic optimization problem. First, we use a specification that is consistent with Gaur et al. (2005) and the following literature to study the determinants of inventory turnover and to compute adjusted inventory turnover on our data. Second, we add estimated productivity and shopping quality as measures of store heterogeneity. Third, we extend the analysis by using an empirical specification that is entirely consistent with endogenous inventory turnover and long-run profit maximization. Our specification is derived using managers' optimal choices while controlling for demand and economies of scale, and it provides a direct link between store productivity and inventory performance.

Our results confirm the empirical findings in the operations management literature using inventory turnover, which is defined as the cost of goods sold over inventory, as the dependent variable (Gaur et al., 2005). The figures in Table 6 show a positive correlation between inventory turnover and capital intensity and a negative correlation between inventory turnover and gross margins. We use previous sales and its squared term to control for store size, and we use sales growth to control for economies of scale and scope. The joint test of the coefficients of previous sales equal zero rejects the null hypothesis, indicating a positive association between store size and inventory turnover. The existence of economies of scale and scope explains the positive correlation between inventory turnover and store size (Shockley and Turner, 2015). The coefficient of store size squared is negative, which implies that there are diminishing returns to scale as store size increases. The coefficient on sales growth is positive but insignificant at conventional levels.[38] All specifications control for fixed effects for year and sub-sector.

By adding store productivity and shopping quality (i.e., measures of store heterogeneity) as controls, we investigate the extent to which these variables explain the variation in inventory turnover. The second specification in Table 6 shows positive and statistically significant coefficients of both productivity and shopping quality. A 10 percent increase in productivity for the median store increases inventory turnover by 3 percent. Consumers' perceived shopping quality has a small positive effect on inventory turnover. We expect this result because the gross margin (included as a control variable) and shopping quality are correlated, and both affect demand. After controlling for store heterogeneity, the negative correlation between gross margins and inventory turnover decreases, and the positive correlation between inventory turnover and capital intensity increases. That the recovered ω_{jt} and μ_{jt} comprise information about previous store performance

[38]The effects are not causal. Several of the explanatory variables are endogenous because they are correlated with supply and demand shocks that are part of the residual. Previous sales are commonly used as a measure of store size in the inventory management literature. Gaur et al. (2005) use an expected measure of sales surprises as an explanatory variable instead of sales growth.

makes the coefficient of store size (lagged sales) statistically insignificant.[39]

Productivity and shopping quality still have explanatory power when using adjusted inventory turnover as an output measure, as suggested by Gaur et al. (2005) (online Appendix C). We conclude that our recovered measures of store-level heterogeneity are essential even when using the more restrictive measure of inventory turnover, i.e., adjusted inventory turnover controls for gross margin, capital intensity and sales surprises. In summary, the findings undoubtedly suggest that store productivity and shopping quality are two additional key factors that increase inventory turnover in addition to the factors emphasized in the operations management literature.

Endogenous inventory turnover. Table 7 shows the specification that is consistent with the structural dynamic model in Section 2, that is, inventory turnover (cost of goods sold over inventory) is a function of the state variables. To explore the large variation in inventory turnover across and within stores over time, we use OLS and quantile estimators.[40] In particular, we explore the following determinants of inventory turnover: productivity shocks ω_{jt}, shopping quality μ_{jt}, investment, labor, the number of product categories, and local market characteristics.

Both productivity and shopping quality increase inventory turnover, and the magnitude of the marginal effects decline with the level of productivity and shopping quality. Importantly, productivity has a greater effect than shopping quality on inventory turnover in all parts of the distribution. Furthermore, the marginal effects of both productivity and shopping quality are larger for stores with already high inventory turnover. A productivity increase yields an increase in inventory turnover that is 1.5-2 times higher in the 75th percentile than in the 25th percentile. The difference becomes even more evident for an increase in shopping quality, where inventory turnover increases 2-3 times more in the 75th percentile than in the 25th.

Inventory turnover increases when a store invests in technology. The marginal effect of investment is approximately twice as large in the 75th percentile than at the median or in the 25th percentile of inventory turnover. Market size and population density have a positive and statistically significant impact on inventory turnover. Moreover, stores with low inventory turnover benefit relatively more from market size expansions (i.e., increase in population). These results are consistent with previous work on productivity, market size, and population density (Syverson, 2004; Syverson, 2011).

In summary, the findings emphasize that store productivity plays a crucial role in increasing inventory turnover. Consumers' perceived shopping quality also improves inventory turnover, but the marginal effect is lower than the effect of productivity. For improvements in both productivity and shopping quality, stores with already high inventory turnover benefit the most.

4.3 Heterogeneity across local markets

Managerial decisions and store outcomes might be determined not only by store-specific variables but also by competitors and characteristics of local markets. To measure local competition, we sum rival stores' productivity and shopping quality in the five-digit SNI industry in the local market and year. Local markets are divided into small and large markets based on the median population (population variables are thus excluded from the regressions). Table 8 shows the re-

[39] This result is because ω_{jt} and μ_{jt} follow AR(1) processes and include information about previous store sales.

[40] Section 6 shows that the results remain robust when using adjusted inventory turnover as an output measure, i.e., the residual in the inventory turnover regression when controlling for differences in gross margin, capital intensity, store size and store size squared (Gaur et al., 2005).

sults of the effect of local competition on inventory, inventory turnover, the number of product categories and market share using the state variables as controls. Even if we do not use a game-theoretic framework, these reduced-form regressions remain consistent with our dynamic model when adding competition variables.[41]

A high-quality shopping experience among competitors implies less demand for a store. Stores thus buy less from wholesalers and decrease inventory if their rivals have high demand. In large markets, an increase in rivals' shopping quality decreases inventory turnover, i.e., the cost of goods sold decreases relatively more than inventory. The opposite holds in small markets, that is, rivals' shopping quality increases inventory turnover. A direct effect of increasing competition from rivals' higher shopping quality is that a store's market share decreases.[42] At the same time, stores try to differentiate by offering a greater number of product categories.

Rivals' productivity does not have a statistically significant effect on inventory turnover. However, stores hold high levels of inventory in markets where rival stores have high productivity. A rival's productivity has a larger impact on inventories in small markets than in large markets, which is consistent with the empirical findings of the scarce literature on competition and product variety (inventory) (e.g., Olivares and Cachon, 2009; Watson, 2009; Ren et al., 2011).[43] The number of product categories that a store carries is negatively affected by an increase in rivals' productivity in both market groups. That product variety decreases and inventory increases implies that stores find an optimal product mix that is less likely to run out of stock. Rivals' productivity has a positive effect on the store's market share, which implies that stores benefit from productivity improvements. Online Appendix D shows that the results in Table 8 remain robust when omitting the interaction terms between demand and productivity and the competition measure.

We conclude that the store's productivity and rivals' shopping quality are key determinants of inventory turnover. There are trade-offs involved in which productivity and shopping quality by rivals work in opposite directions when determining inventory and product variety. In particular, an increase in rivals' shopping quality forces stores in small markets to increase their inventory turnover, whereas stores in large markets decrease their inventory turnover.

5 Counterfactual experiments

We use the estimated model to perform several counterfactual policy experiments. Knowledge about the underlying primitives is crucial to be able to simulate changes in store outcomes following hypothetical changes. The counterfactual experiments highlight recent trends in retail businesses and relate directly to the hands-on decisions of managers, offering strong implications for management practices.

To improve business performance, managers face trade-offs between investing to reduce costs

[41] The theoretical framework used to estimate productivity in Olley and Pakes (1996) is consistent with the game theoretical framework presented in Ericson and Pakes (1995).

[42] We investigate the impact on market share without modeling entry and exit. In markets with large store turnover, market shares can increase because of a stronger competition from rivals, i.e., reallocation.

[43] Using data on U.S. General Motors dealerships, Olivares and Cachon (2009) find that dealers hold larger inventories in local markets with more intense competition. Watson (2009) finds that eyewear retailers in the U.S. have more inventory when rivals are located nearby. Using data for all Best Buy and Circuit City stores in the U.S., Ren et al. (2011) find that a store's product variety increases with the presence of rival stores in the market (i.e., more intense competition) but that product variety decreases when stores are co-located (i.e., stores differentiate and select product variety to avoid overlapping with that of rivals).

and stimulating demand in their budget allocation because the outcomes of investments are subject to uncertainty. Providing tools to measure the impact of uncertainty, as this paper does, helps managers to understand these trade-offs. We compare managers' optimal decisions and store outcomes before and after a hypothetical cost reduction (through improvements in productivity) and/or an enhanced customer base (shopping quality). Examples of productivity enhancing activities in retail are investments in new technologies such as self-scanning and new payment systems, technology upgrades, and new software to improve supply chain management. Activities that stimulate the quality of the shopping experience for consumers relate to improved customer service through, for instance, the repositioning of products inside the store, better product information from digitalization, and more specialized employees.

The sign and size of the changes in managers' optimal decisions from a counterfactual experiment are theoretically ambiguous and depend on the trade-off between productivity and shopping quality. For instance, stores face incentives to expand product variety as a result of productivity improvements, whereas product variety may either expand or contract as a result of demand shocks. Particularly, predicting net changes in short- and long-run inventory performance and product variety from hypothetical changes in productivity and demand is not possible without tools that model managers' optimal decisions.

We use the estimated productivity and shopping quality processes together with managers' optimal policy functions to evaluate changes in inventory, inventory turnover, the number of employees, investment, and the number of product categories from a hypothetical change. Furthermore, using the market share equation (4) in Section 2, we compute consumer surplus in local markets under the assumption of a logit demand model and no changes in the characteristics of local markets (i.e., population, population density, and income).[44] For each store, we compute averages of over 100 simulations over five years, starting with the last year in the data.[45] The proposed counterfactual policy experiments assume that the new equilibrium is consistent with the observed equilibrium in the data, which allows us to use the estimated policy functions in the simulations (Bajari et al., 2007).

This paper implements four policy experiments. The first (CF_1) analyzes the impact of positive innovation shocks to productivity, and it is implemented by shifting the mean of ξ_{jt}. The estimated mean of these shocks is close to zero, and the mean is set to 0.05 in CF_1. Second, counterfactual CF_2 adds a decrease in uncertainty in shopping quality innovations to the positive shocks to productivity (CF_1). This counterfactual is implemented to be comparable to CF_1, that is, we reduce the standard deviation of innovations in shopping quality η_{jt} by 30 percent and increase the mean of productivity shocks ξ_{jt} to 0.05. The third counterfactual (CF_3) studies the effect of positive innovations on the quality of the shopping experience. It is implemented similarly to CF_1, i.e., we shift the mean of innovations in shopping quality η_{jt} to 0.05. The fourth counterfactual (CF_4) decreases uncertainty in productivity innovations in addition to increasing shopping quality in CF_3. We implement this counterfactual to be comparable to CF_3. Hence, the standard deviation of innovations in productivity ξ_{jt} decreases by 30 percent, and the mean

[44] Stores that are not in the sample for which we observe product-level information are included in the outside option. We access input and output measures for all stores, whereas the product-level data are available for a sample. See the data section for details (Section 3).

[45] The base simulations use estimated means and standard deviations of the innovations in productivity and shopping quality (i.e., ξ_{jt} and η_{jt}). Using the logit demand system to compute market shares for the years in the data, we predict the observed store market shares well (e.g., the last year in the data), which suggests that the logit demand is not a restrictive assumption in our case, although cross-price elasticities are not the primary focus of this paper (Berry, 1994).

of innovations in shopping quality η_{jt} is set to 0.05.

Table 9 shows the mean and interquartile range of the changes in inventory at the end of the year, inventory turnover, the number of employees, investments, the number of products, and consumer surplus.[46] The dynamic nature of our theoretical model allows the counterfactual simulations to explore both short- and long-run implications following hypothetical changes in productivity and/or shopping quality. We discuss the changes in store decisions and outcomes after one, three, and five years in detail.

5.1 Counterfactual I: Innovations in productivity

The direct effect of improving productivity (CF_1) is an increase in the volume of transactions, which affects not only sales but also the store's input choices, the number of products and inventory (Holmes, 2001). The findings show that higher productivity connects to more labor, investments and inventories to support store growth. The productivity increase corresponds to a 1.5 percent increase in the number of employees in the coming year and a 9.4 percent increase after five years. The demand for investments increases by 3 percent in the coming year, reaching up to 20 percent after five years. Inventories at the end of the year also increase. Inventory turnover increases by 1.7 percent in the first year and increases up to 2.6 percent after five years.

The number of products and consumer surplus increase slightly. On average, the number of products increases by 1.2 percent after one year and by 2 percent after five years. The finding that both inventory at the end of year and the number of product categories increase suggests that stores use cost savings from productivity improvements to ensure that consumers access a larger product variety.

In summary, our simulations in CF_1 confirm that productivity is a crucial determinant of inventory turnover. Productivity innovations yield more labor and investments and only a small increase in the number of product categories. Hence, inventory turnover grows relatively more than the number of product categories.

5.2 Counterfactual II: Innovations in productivity and reduced uncertainty in shopping quality innovations

The second policy experiment CF_2 adds a reduction in the dispersion of shopping quality innovations to CF_1 (i.e., it reduces the extreme values in the shopping quality received by stores). Reducing uncertainty in shopping quality innovations makes stores specialize in the short run and increase the number of product categories in the long run (about 12 percent after five years). In the short run, stores specialize because even if they might receive positive innovations in shopping quality, they are not large enough to shift the potential demand. As a result, stores face stronger competition, which makes them reposition. In the long run, there is room for market expansion because stores can predict demand and productivity changes more accurately as a result of reducing uncertainty. Consumer surplus follows the same pattern and increases about 2 percent after five years.

[46] Following Small and Rosen (1981), the consumer surplus in market m in period t is computed from equation (4) $W_{mt} = M \times ln(\sum_j exp(\rho_{np} np_{jt}(\mathbf{s}_{jt}) + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc^2_{mt} + \mu_{jt}))/\sigma$, where M is market size (population) and $np_{jt}(\mathbf{s}_{jt})$ is the predicted number of product categories using the store's state variables $\mathbf{s}_{jt}$.

Stores hire and invest in technology more when uncertainty in demand is reduced, which implies that local communities benefit because stores hire more.[47] Both inventory and inventory turnover increase. There is clear evidence that inventory turnover increases more in CF_2 than in CF_1, which is especially true in the long run, where inventory turnover increases by about 7 percent after 5 years. By reducing the uncertainty in shopping quality, stores avoid drops in shopping quality that accumulate over time and affect future productivity. For example, avoiding a decrease in shopping quality due to consumers' misunderstanding about product information reduces the amount of time that employees spend on nonproductive tasks, such as searching for the right information or product.

In summary, stores benefit more from reducing uncertainty in shopping quality innovations and receiving positive productivity shocks than from receiving only positive productivity shocks. We conclude that both higher productivity and lower dispersion in shopping quality are crucial for increasing inventory turnover over time, highlighting the importance of recovering two types of store-level heterogeneity (productivity and shopping quality) and understanding their relationship as we do in our dynamic model.

5.3 Counterfactual III: Innovations in shopping quality

The third policy experiment (CF_3) increases the mean of innovations in shopping quality, i.e., the mean of η_{jt}. Because the average shopping quality increases by the same magnitude in CF_3 as innovations in productivity increase in CF_1 and CF_2, these counterfactuals are directly comparable. The direct effect is that consumers are more willing to buy from a store that increases sales. Investment, labor, inventories, and inventory turnover increase, but the changes are substantially lower than in the policy experiments that increase the mean of innovation shocks in productivity (CF_1 and CF_2). For instance, the increase in labor in CF_3 is only about one-third of that in CF_1 (i.e., labor increases 0.4 percent in the coming year, 1.5 percent after three years, and about 3 percent after five years). Inventory turnover experiences an increase below 1 percent on average in the short-run, which is indeed distinctively lower than the outcomes when productivity shocks increase.

The simulations show that the number of product categories decreases, i.e., there is an increase in store-level specialization on average. The increase in consumer surplus is about double than in the experiments that raise productivity (CF_1 and CF_2). Thus, consumer surplus increases even if stores specialize and offer fewer product categories. Store shopping quality drives this increase in consumer surplus. Given that the shopping quality comprises various factors that increase consumer satisfaction to buy but that are unobservable to the researcher (e.g., shopping experience, product quality, etc.), our findings suggest that store size expansion and performance improvements can be slow if managers target only consumer satisfaction without considering productivity improvements.

[47] Note that this benefit is not part of our consumer surplus measure.

5.4 Counterfactual IV: Innovations in shopping quality and reduced uncertainty in productivity innovations

The policy experiment CF_4 adds to CF_3 a 30 percent reduction in the standard deviation of the innovation shock in productivity (i.e., ξ_{jt}). That is, stores experience an average increase in shopping quality μ_{jt} and fewer extreme innovation shocks in productivity. Because the possibility to gain large improvements in productivity decreases and productivity depreciates yearly (property of an AR(1) process), stores reduce their labor force (about 1.5 percent after three years, and 8.5 percent after five years). Investments decline in the short run but rise in the long run. Therefore, stores substitute labor for capital in the long run. This substitution pattern highlights the importance of productivity improvements for store development.

There is a small increase in inventory turnover in CF_4 compared to CF_3, driven mainly by avoiding large drops in productivity. Moreover, because of reduced uncertainty in productivity, the growth in inventories at the end of the year is smaller than in CF_3. By raising shopping quality consumers benefit and extract more surplus, and stores increase specialization (similar to CF_3).

We conclude that stores specialize and reduce employment after decreasing uncertainty in productivity and increasing the level of shopping quality. Inventory turnover increases only slightly. In the long run, stores experience a labor-capital substitution. Most importantly, stores do not hire or invest as much as in policy experiments that raise productivity, which also dampens inventory performance.

5.5 Counterfactuals: Managerial implications

The trade-off between store productivity and shopping quality in the counterfactuals is important for understanding the factors that affect inventory behavior and product variety. While the estimated policy functions also highlight this trade-off, an advantage of the counterfactuals is that they exploit the impact of uncertainty in the short and long run. This situation has implications not only for inventory behavior but also for other managerial decisions related to, for instance, changes in store size and product assortment.

The results from all four counterfactual experiments together point to productivity being key to driving inventory turnover and product variety. Shopping quality, on the other hand, induces only minor improvements in inventory turnover if it is not sustained together with productivity improvements. Our results have a straightforward connection to the theoretical findings in Holmes (2001).

Our insights speak to a clear link between a store's total factor productivity and inventory turnover, which is strengthened if combined with shopping quality that is more appealing to consumers. Managers can indeed ensure that inventory turnover climbs to high levels by actively being involved in activities that improve productivity and reduce consumers' uncertainty in perceived shopping quality. In this manner, our results directly serve managers in their decision process to boost inventory performance.

6 Robustness

This section discusses the robustness of the results using alternative modeling specifications.

Estimation of the service generating function. The labor and the cost of products bought are used as proxy variables to recover productivity and shopping quality. However, instead of labor demand, the investment demand function can be used to recover productivity. The estimation results remain robust when using investment as a proxy, e.g., the estimated persistence in productivity and shopping quality is similar to our main results. Most importantly, productivity is still the main driver of a store's choices. We prefer the specification using labor demand because it uses all observations in the data and does not require positive investments.

The identification of the model uses the variables in $t-1$ as instruments (Ackerberg et al., 2007). The estimates do not change when using local market variables in the current period t as instruments. The persistence of productivity increases if the sales of other product categories in period t (y_{-ijt}) are used as an instrument. As we expect, this finding indicates that the moment condition based on y_{-ijt} does not hold and affects the identification of all parameters of the sales generating function. For this reason, using y_{-ijt-1} as an instrument is a better choice.

Adjusted inventory turnover. The positive effects of productivity and shopping quality in the quantile regressions in Table 7 remain robust when using adjusted inventory turnover as an output measure (online Appendix C). Again, the results show that productivity is the main factor that shifts inventory turnover, especially for stores in the lower percentiles. Investments are more effective in increasing inventory turnover for stores in the upper percentiles.

Inventory, market size, and competition. The results for inventory, market size, and competition in Table 8 remain robust using the specification that omits the quadratic terms of the competition variables. The most important result is that in both market groups, a store's own productivity is the main driver of improvements in inventory turnover. Stores in small markets with intense competition from rivals (i.e., rivals' productivity and shopping quality) have higher inventory turnover. This finding suggests that surviving stores learn from increasing competitive pressure to improve inventory efficiency. Importantly, the impact of rivals' productivity on inventory is about double that of rivals' demand. Again, the impact of rivals' competition on inventory turnover is small (and not statistically significant for productivity) in large markets.

Rivals' productivity and shopping quality are not important in large markets, but they play different roles in small markets. In those markets, with stronger competitive pressure from rivals' productivity, stores specialize, i.e., they decrease the number of product categories. Furthermore, if the rivals offer a high-quality shopping experience, then a store offers more product categories to counterbalance the drop in market share.

Alternative counterfactual experiments. The fifth counterfactual experiment (CF_5) evaluates positive shocks to productivity to compensate for negative shopping quality. CF_5 assumes that stores experience larger positive shocks to productivity than in CF_1, i.e., the shocks in productivity are four times larger than the negative shocks to demand. That is, we increase the mean of ξ_{jt} to 0.2 and decrease the mean of ν_{jt} to -0.05. Due to productivity improvements, stores grow in size (labor) and expand their product categories. Consumers experience more product variety to compensate for the negative effect caused by the decrease in shopping quality μ. The detailed results from this alternative counterfactual are presented in online Appendix E, which also discusses the heterogeneity across markets in the counterfactual experiments.

7 Conclusions

The relationship between inventory behavior and output has attracted a great deal of attention among economists. Understanding why stores have different inventory levels and the role of inventories has been on the research agenda since the 1940-50s (e.g., Working, 1949; Brennan, 1958). However, there is little research on the role of store productivity and demand shocks related to consumers' shopping quality in inventory behavior, product variety and overall store performance.

This paper uses a dynamic model based on a rich multi-product sales technology and a demand system to estimate total factor productivity and demand shocks related to shopping quality and to analyze the implications for inventory behavior and product variety. In our model, managers strategically adjust inventory holdings and make input choices of labor and investments in technology based on their productivity, consumers' perceived shopping quality, and the local market environment. We estimate the model using novel data on a store's inputs, outputs, inventories, products bought from the wholesaler, and product variety in the retail sale of new goods in specialized stores in Sweden from 2003 to 2009. Important contributions to the existing literature are that we recover two unobserved store-level shocks, account for multi-product retailers, allow stores to learn about demand to improve future productivity, and endogenize inventory behavior and inventory performance. The model is used to investigate the underlying theoretical primitives behind inventory performance and to perform counterfactual experiments that evaluate managers' optimal responses to changes in levels and the uncertainty of productivity and shopping quality.

We model and find empirical evidence of stores learning from consumers' perceived quality of the shopping experience to produce process innovations that increase future productivity. This finding relates to recent investments in technology that help retailers to collect data that are utilized for a better understanding of consumer preferences.

The proposed modeling framework endogenizes managers' decisions related to inventory behavior and product variety. Our findings show that store-level shocks (productivity and shopping quality), internal factors (e.g., store investment and labor), and the external environment (local market demand and competition) are important primitives behind the observed heterogeneity in inventory performance. Store productivity is the main determinant of inventory turnover. Hence, productivity has a positive impact on inventory turnover, and this effect is larger in the upper percentiles. Shopping quality also increases inventory turnover but at a substantially lower magnitude than productivity. Rivals' shopping quality in the local market is, however, an important determinant of inventory turnover, whereas more intense competition from rivals' productivity increases inventory holdings, especially in small markets. Further, a store's own investments, the local market size, and population density improve inventory turnover.

Higher productivity makes stores broaden product variety, hold larger inventories, and invest more in new technology. This finding suggests that productivity drives product expansion in stores. Managers' optimal choice of products also depends on whether the store currently offers a high- or low-quality shopping experience. Hence, high-quality stores can handle wider product variety, whereas low-quality stores need to specialize in selling fewer products.

The counterfactual experiments show that positive innovations in productivity lead to an increase in inventory turnover, and this effect is larger when reducing uncertainty in demand. Inventory turnover increases three times more when uncertainty in demand is reduced than when it is not. The counterfactual that stimulates shopping quality and lower uncertainty in productivity results in only a modest increase in inventory turnover. However, in the long run, stores substitute labor for capital. Positive shocks to productivity result in wider product variety, especially in the long run and when reducing uncertainty in demand. Stores also hire more due to productivity improvements when demand uncertainty is reduced.

Our findings serve as a direct basis for managerial decisions and can be used in the daily activities of retail managers to improve store performance. Although our suggested modeling framework is applied to detailed data on Swedish retailers, our analysis has broad implications for retailers more generally. First, our insights speak to a clear link between store total factor productivity and inventory turnover that is strengthened if combined with shopping quality that is more appealing to consumers. Managers can indeed ensure that inventory turnover climbs to high levels by actively being involved in activities that improve productivity and reduce consumers' uncertainty in perceived shopping quality. To focus only on productivity does not improve inventory turnover equally and to only increase shopping quality leads to sharply lower inventory turnover. Second, managers should also target productivity improvements because they are a key driver of product diversity inside the store. Learning from demand and investing in new technologies, such as scanners and mobile payment systems, will drive productivity improvements and thus ensure broader product diversity for consumers. Third, demand and more intense competition in local markets will also be important for managers to monitor. Rivals' shopping quality in local markets influences inventory turnover, whereas rivals' productivity increases inventory holdings – this outcome is most pronounced in small markets. Taken together, our findings highlight new trade-offs between supply and demand that have direct managerial implications. In future research, the multi-product framework can be extended to fully model the dynamics of the number of products and the importance of stores' cost structure for inventory behavior and store performance.

References

Ackerberg, D., L. Benkard, S. Berry, and A. Pakes (2007): *Handbook of Econometrics,*, Elsevier, vol. 6, chap. Econometric Tools for Analyzing Market Outcomes, 4171–4276.

Ackerberg, D., K. Caves, and G. Fraser (2015): "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83, 2411–2451.

Ackerberg, D., X. Chen, and J. Hahn (2012): "A Practical Asymptotic Variance Estimator for Two-Step Semiparametric Estimators," *Review of Economics and Statistics*, 94, 481–498.

Aguirregabiria, V. (1999): "The Dynamics of Markups and Inventories in Retailing Firms," *The Review of Economic Studies*, 66, 275–308.

Alan, Y., G. P. Gao, and V. Gaur (2014): "Does Inventory Proeuctivity Predict Future Stock Returns? A Retailing Industry Perspective," *Management Science*, 60, 2416–2434.

Amihud, Y. and H. Mendelson (1989): "Inventory Behavior and Market Power: An Empirical Investigation," *International Journal of Industrial Organization*, 7, 269–280.

Anderson, S. and A. De Palma (2006): "Market performance with multi-product firms," *Journal of Industrial Economics*, 54, 95–124.

Anderson, S., A. De Palma, and J. F. Thisse (1987): "The CES is a discrete choice model?" *Economics Letters*, 24, 139–140.

Bajari, P., L. Benkard, and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 75, 1331–1370.

Basker, E. (2015): "Change at the Checkout: Tracing the Impact of a Process Innovation," *Journal of Industrial Economics*, 63, 339–370.

Bernstein, F. and A. Federgruen (2005): "Decentralized Supply Chains with Competing Retailers under Demand Uncertainty," *Management Science*, 51, 18–29.

Berry, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 25, 242–262.

Berry, S., A. Eizenberg, and J. Waldfogel (2016): "Optimal Product Variety in Radio Markets," *RAND Journal of Economics*, 47, 463–497.

Berry, S. and J. Waldfogel (2010): "Product Quality andf Market Size," *The Journal of Industrial Economics*, 58, 1–31.

Blinder, A., M. Lovell, and L. Summers (1981): "Retail Inventory Behavior and Business Fluctuations," *Brookings Papers on Economic Activity*, 2, 443–520.

Blinder, A. and L. Maccini (1991): "Taking Stock: A Critical Assessment of Recent Research on Inventories," *Journal of Economic Perspectives*, 5, 73–96.

Braguinsky, S., A. Ohyama, T. Okazaki, and C. Syverson (2015): "Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry," *American Economic Review*, 105, 2086–2119.

Brennan, M. J. (1958): "The Supply of Storage," *The American Economic Review*, 48, 50–72.

Cachon, G., S. Galino, and M. Olivares (2018): "Does Adding Inventory Increase Sales? Evidence of a Scarcity Effect in U.S. Automobile Dealerships," *Management Science, forthcoming.*

Cachon, G. and M. Olivares (2010): “Drivers of Finished-Goods Inventory in the U.S. Automobile Industry,” *Management Science*, 56, 202–2016.

Cachon, G. and C. Terwiesch (2005): *Matching Supply with Demand: An Introduction to Operations Management*, The McGraw-Hill Companies, second edition ed.

Coen-Pirani, D. (2004): “Markups, Aggregation, and Inventory Adjustment,” *The American Economic Review*, 94, 1328–1353.

De Loecker, J. (2011): “Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity,” *Econometrica*, 79, 1407–1451.

De Loecker, J., P. Goldberg, A. Khandelwal, and N. Pavcnik (2016): “Prices, Markups, and Trade Reform,” *Econometrica*, 84, 445–510.

Dhyne, E., A. Petrin, V. Smeets, and F. Warzynski (2017): “Multi-Product Firms, Import Competition, and the Evolution of Firm-Product Technical Efficiencies,” Mimeo, University of Minnesota.

Doraszelski, U. and J. Jaumandreu (2013): “R&D and Productivity: Estimating Endogenous Productivity,” *Review of Economic Studies*, 80, 1338–1383.

Ericson, R. and A. Pakes (1995): “Markov-Perfect Industry Dynamics: A Framework for Empirical Work,” *Review of Economic Studies*, 62, 53–83.

Gandhi, A., S. Navarro, and D. Rivers (2018): “On the Identification of Production Functions: How Heterogenous is Productivity?” *Forthcoming, Journal of Political Economy.*

Gaur, V., L. Fisher, M, and A. Raman (2005): “An Econometric Analysis of Inventory Turnover Performance in Retail Services,” *Management Science*, 51, 181–194.

Gaur, V., S. Kesavan, and A. Raman (2014): “Retail Inventory: Managing the Canary in the Coal Mine,” *California Management Review*, 56, 55–76.

Hendel, I. and A. Nevo (2006): “Measuring the Implications of Sales and Consumer Inventory Behavior,” *Econometrica*, 74, 637–1673.

Holmes, T. J. (2001): “Bar Codes Lead to Frequent Deliveries and Superstores,” *The RAND Journal of Economics*, 32, 708–725.

Hortacsu, A. and J. Joonhwi (2015): “Semiparametric Estimation of CES Demand System with Observed and Unobserved Product Characteristics,” *Mimeo, University of Chicago.*

Humphreys, B., L. Maccini, and S. Schuh (2001): “Input and Output Inventories,” *Journal of Monetary Economics*, 47, 347–375.

Iacoviello, M., F. Schiantarelli, and S. Schuh (2011): “Input and Output Inventories in General Equilibrium,” *International Economic Review*, 52, 1179–1213.

Jerath, K., S.-H. Kim, and R. Swinney (2017): “Product Quality in a Distribution Channel with Inventory Risk,” *Management Science*, 36, 645–812.

Kesavan, S., V. Gaur, and A. Raman (2011): “Incorporating Price and Inventory Endogeneity in Firm Level Sales Forecasting,” *Management Science*, 56, 1519–1533.

Kesavan, S. and V. Mani (2013): “The Relationship Between Abnormal Inventory Growth and Furutre Earnings for US Public Retailers,” *Manufacturing and Serive Operations Management*, 15, 6–23.

Khan, A. and J. Thomas (2007): “Inventories and the Business Cycle: An Equilibrium Analysis of (S,s) Policies,” *American Economic Review*, 97, 1165–1188.

Klette, T. and Z. Griliches (1996): "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous," *Journal of Applied Econometrics*, 11, 343–361.

Kumar, P. and H. Zhang (2018): "Productivity or Unexpected Demand Shocks: What Determines Firms' Investment and Exit Decisions?" *Forthcoming, International Economic Review.*

Levinsohn, J. and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70, 317–341.

Liberman, M. B., S. Helper, and L. Demeester (1999): "The Empirical Determinants of Inventory Levels in High-Volume Manufacturing," *Production and Operations Management*, 8, 44–55.

Lieberman, M. and L. Demeester (1999): "Inventory Reduction and Productivity Growth: Linkages in the Japanese Automotive Industry," *Management Science*, 45, 466–485.

Maican, F. and M. Orth (2015): "A Dynamic Analysis of Entry Regulations and Productivity in Retail Trade," *International Journal of Industrial Organization*, 40, 67–80.

——— (2017): "Productivity Dynamics and the role of "Big-Box" Entrants in Retailing," *Journal of Industrial Economics*, LXV, 397–438.

——— (2018): "Entry Regulations, Product Variety, and Inventories in Retail Trade," *Mimeo, Research Institute of Industrial Economics.*

Matsa, D. (2011): "Competition and Product Quality in the Supermarket Industry," *Quarterly Journal of Economics*, 126, 1539–1591.

Mundlak, Y. (1964): "Transcendental Multiproduct Production Functions," *International Economic Review*, 5, 273–284.

Olivares, M. and G. Cachon (2009): "Competing retailers and inventory: An empirical investigation of General Motors' dealerships in isolated markets." *Marketing Science*, 12, 165–176.

Olley, S. and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64, 1263–1297.

Pakes, A. (1994): chap. The Estimation of Dynamic Structural Models: Problems and Prospects Part II. Mixed Continuous-Discrete Control Models and Market Interactions, Laffont, J. J. and Sims, C. eds, Advances in Econometrics: Proceedings of the 6th World Congress of the Econometric Society, Chapter 5.

Pindyck, R. (1994): "Inventories and the Short-Run Dynamics of Commodity Prices," *RAND Journal of Economics*, 25, 141–159.

Rajagopalan, S. (2012): "Impact of Variety and Distribution System Characteristics on Inventory Levels at US Retailers," *Manufacturing and Service Operations Management*, 15, 191–204.

Raman, A. (2012): *The Future of Retail*, Harvard Business School Publishing, chap. Retailers Beware: Markets Punish Stores with Too Much Inventory, 7–8.

Ramey, V. A. (1989): "Inventories as Factors of Production and Economic Performance," *The American Economic Review*, 79, 338–354.

Ramey, V. A. and K. D. West (1999): *Handbook of Macroeconomics*, Elsevier, vol. 1, chap. Inventories, 863–923.

Ren, C., Y. Hu, Y. Hu, and J. Hausman (2011): "Managing Product Variety and Collocation in a Competitive Environment: An Empirical Investigation of Consumer Electronics Retailing," *Management Science*, 57, 1009–1024.

Rumyantsev, S. and S. Netessine (2007): "What Can Be Learned from Classical Inventory Models? A Cross-industry Exploratory Investigation," *Manufacturing and Serive Operations Management*, 9, 409–429.

Scherer, F. M. and D. Ross (1990): *Industrial Market Structure and Economic Performance*, Houghton Mifflin Company.

Seiler, S. (2013): "The Impact of Search Costs on Consumer Behavior: A Dynamic Approach," *Quantitative Marketing and Economics*, 11, 155–203.

Serpa, J. and H. Krishnan (2017): "The Impact of Supply Chains on Firm-Level Productivity," *Management Science*, 64, 1–22.

Shockley, J. and T. Turner (2015): "Linking Inventory Efficiency, Productivity and Responsiveness to Retail Firm Outperformance: Empirical Insights from US Retailing Segments," *Production Planning & Control*, 26, 393–406.

Small, K. A. and H. S. Rosen (1981): "Applied Welfare Economics with Discrete Choice Models," *Econometrica*, 49, 105–130.

Syverson, C. (2004): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112, 1181–1222.

——— (2011): "What Determines Productivity?" *Journal of Economic Literature*, 49, 326–365.

van Ryzin, G. and S. Mahajan (1999): "On the Relationship Between Inventory Costs and Variety Benefits in Retail Assortments," *Management Science*, 45, 1496–1509.

Watson, R. (2009): "Product variety and competition in the retail market for eyeglasses." *Journal of Industrial Economics*, 57, 217–251.

Wen, Y. (2011): "Input and Output Inventory Dynamics," *American Economic Journal: Macroeconomics*, 3, 181–212.

Wooldridge, J. M. (2009): "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," *Economics Letters*, 104, 112–114.

Working, H. (1949): "The Theory of Price of Storage," *The American Economic Review*, 39, 1254–1262.

Table 1: Descriptive statistics

Year	No. of stores	Sales	Value added	Inventory	Investment	No. of employees	Mean number of product categories at store level
2004	587	80.454	17.518	64.811	1.286	31,424	3.101
2005	1,139	97.144	22.358	71.277	1.531	39,468	4.514
2006	1,006	103.116	23.448	73.294	1.796	38,640	4.151
2007	1,137	147.852	30.497	112.757	2.466	47,104	4.399
2008	1,180	130.613	26.427	89.820	2.528	49,130	4.185
2009	1,055	131.826	27.123	91.975	2.335	47,940	4.223

NOTE: Sales (excl. VAT), value added, inventories (includes products bought), and investment are measured in billions of 2000 SEK (1 USD= 7.3 SEK, 1 EUR= 9.3 SEK). The number of employees is measured in thousands.

Table 2: Estimation of the multi-product sales generating function

	OLS		Two-step estimation	
	Estimate	Std.	Estimate	Std.
Log no. of employees	0.7866	0.0290	0.5394	0.0421
Log of capital	0.0599	0.0129	0.3376	0.0274
Log of inventory	1.0367	0.0212	0.4398	0.0233
Log of sales of other products	-0.8959	0.0098	-0.8569	0.0113
Log of sales outside option	-0.0055	0.0065	0.2177	0.013
Log of population	0.0233	0.0218	-0.0321	0.032
Log of population density	0.0076	0.0151	0.3222	0.032
Log of income	34.7509	13.2213	0.7768	0.058
Log of income squared	-3.2989	1.2435	-0.0450	0.015
Coef. of no. of products (ρ_{np})			0.2169	0.0341
Demand elasticity ($1/\sigma$)			4.592	
Year fixed-effect	Yes		Yes	
No. of obs.	16,759		16,759	

NOTE: The dependent variable is the log of sales of a product category at the store level. Labor is measured as the number of full-time adjusted employees. Sales of other product categories are measured at the store level. Sales of the outside option measures total sales of the other products of all other five-digit SNI codes at the local market. All regressions include year dummies and five-digit SNI dummies. *OLS* refers to an ordinary least squares regression. Two-step estimation refers to the extended Olley and Pakes (1996) estimation method presented in Section 2 (Maican and Orth, 2018). Reported standard errors (in parentheses) are computed using Ackerberg et al. (2012).

Table 3: Estimation of structural parameters: Productivity and demand shock processes

Productivity (ω_t) process	Estimate	Std.	Shopping quality (μ_t) process	Estimate	Std.
Productivity (ω_{t-1})	0.9395	0.0426	Shopping quality (μ_{t-1})	0.8589	0.0258
Productivity squared (ω_{t-1}^2)	-0.0202	0.0163	Shopping quality squared (μ_{t-1}^2)	-0.0197	0.0023
Productivity cubic (ω_{t-1}^3)	-0.0034	0.0018	Shopping quality cubic (μ_{t-1}^3)	-0.0006	0.0002
Prod.*Ext. shock ($\omega_{t-1} \times \mu_{t-1}$)	0.0186	0.0028			
External shock (μ_{t-1})	0.0914	0.0116			
Year fixed-effects	Yes		Year fixed-effects	Yes	
Sub-sector fixed-effects	Yes		Year fixed-effects	Yes	
Adjusted R-squared	0.983		Adjusted R-squared	0.837	
Coefficients of ω_{t-1} terms are zero	F-test	p-value			
	424.139	0.000			
Coefficients of μ_{t-1} terms are zero	F-test	p-value			
	27.713	0.000			
Persistence ($d\omega_t/d\omega_{t-1}$)	0.871		Persistence ($d\mu_t/d\mu_{t-1}$)	0.941	
Effect of shopping quality ($d\omega_t/d\mu_{t-1}$)	0.018				

NOTE: Productivity is estimated using the two-step estimation method in Section 2. Mean values are presented for the marginal effects.

Table 4: Estimation of the investment, labor, and inventory policy functions

	Log of investment (i_t)		Log of labor (l_t)		Log of products and inventories (a_t)		Log of inventories end of year (n_{t+1})	
	Estimate	Std.	Estimate	Std.	Estimate	Std.	Estimate	Std.
Productivity (ω_t)	0.9724	0.0750	0.3680	0.0220	0.3428	0.0202	0.2281	0.0225
Productivity squared ($(\omega_t)^2$)	0.0910	0.0112	0.0178	0.0033	-0.0089	0.0030	0.0197	0.0033
Shopping quality (μ_t)	0.0028	0.0166	0.0602	0.0049	0.0671	0.0044	0.0612	0.0050
Shopping quality squared ($(\mu_t)^2$)	-0.0023	0.0016	0.0047	0.0004	-0.0058	0.0004	-0.0049	0.0004
Log of prev. investment (i_{t-1})	0.2559	0.0158	0.0870	0.0046	0.0340	0.0042	0.0249	0.0047
Log of prev. capital (k_{t-1})	0.1394	0.0240	0.2711	0.0070	0.1957	0.0064	0.0867	0.0072
Log of inventories (n_t)	0.1564	0.0323	0.2381	0.0095	0.4155	0.0087	0.6927	0.0097
Log of population (pop_t)	-0.0209	0.0475	0.0900	0.0139	0.0824	0.0128	0.0746	0.0143
Log of pop. density ($popdens_t$)	0.0848	0.0288	0.0546	0.0084	0.0771	0.0077	0.0455	0.0086
Log of income (inc_t)	-0.6249	0.3996	0.2914	0.1173	0.0150	0.1076	0.0506	0.1202
Year fixed-effects	Yes		Yes		Yes		Yes	
Sub-sector fixed-effects	Yes		Yes		Yes		Yes	
Adjusted R-squared	0.484		0.921		0.954		0.942	

NOTE: The dependent variables are the log of investment in capital (i_t), the log of the sum between the inventories at the beginning of the year (n_t) and the cost of products bought during the year (a_t), and the log of inventories at the end of the year (n_{t+1}). All regressions include an intercept and control for the average wage. Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Table 5: The impact of store and market characteristics on product category

Dependent variable	No. product categories (np_{jt})		HHI product categories in a store		No. of unique product categories in a market	
	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	1.2393	0.1042	-0.0890	0.0117	0.1944	0.0765
Productivity squared ($(\omega_t)^2$)	-0.0172	0.0158	0.0019	0.0017	0.0123	0.0107
Shopping quality (μ_t)	-0.6090	0.0253	0.0437	0.0028	-0.0927	0.0145
Shopping quality squared ($(\mu_t)^2$)	0.0529	0.0023	-0.0037	0.0002	0.0077	0.0015
Log of investment (i_{t-1})	0.4429	0.0349	-0.0369	0.0039	0.0250	0.0172
Log of capital (k_{t-1})	0.0888	0.0230	-0.0016	0.0026	0.0199	0.0231
Log of inventories (n_t)	-0.0636	0.0448	0.0029	0.0050	-0.0290	0.0283
Log of population (pop_t)	-1.1874	0.0700	0.0888	0.0078	0.7312	0.0407
Log of population density ($popdens_t$)	-0.0136	0.0417	0.0010	0.0047	-0.0412	0.0245
Log of income (inc_t)	-0.3764	0.5854	0.0457	0.0659	-0.7159	0.3757
Year fixed-effects	Yes		Yes		Yes	
Sub-sector fixed-effects	Yes		Yes		Yes	
Adjusted R-squared	0.513		0.403		0.647	

NOTE: Productivity and shopping quality are estimated using the two-step estimation method in Section 2. In the third specification, the median for each variable is computed at the local market level. Store regressions control for the average wage. The intercept is included in all specifications.

Table 6: Determinants of inventory turnover in retail

	Model 1		Model 2	
	Est.	Std.	Est.	Std.
Productivity (ω_t)			0.2301	0.0496
Productivity squared ($(\omega_t)^2$)			-0.0171	0.0062
Shopping quality (μ_t)			-0.0167	0.0097
Shopping quality squared ($(\mu_t)^2$)			0.0020	0.0008
Log of gross margin (gm_t)	-0.6382	0.0417	-0.5409	0.0401
Log of capital intensity (ci_t)	0.2935	0.0170	0.4170	0.0181
Store size (y_{t-1})	0.0475	0.0320	-0.0327	0.0365
Store size squared (y^2_{t-1})	-0.0062	0.0036	-0.0139	0.0040
Sales growth ($y_t - y_{t-1}$)	0.0800	0.0520	-0.1007	0.0523
Year fixed-effects	Yes		Yes	
Sub-sector fixed-effects	Yes		Yes	
Local market fixed-effects	Yes		Yes	
Adjusted R-squared	0.504		0.558	

NOTE: The dependent variable is the log of inventory turnover (cost of goods sold over average inventory). Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Table 7: Determinants of inventory turnover in retail

	OLS		Quantile regression					
			Q25		Q50		Q75	
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	0.2222	0.0333	0.1717	0.0295	0.2171	0.0474	0.2917	0.0595
Productivity squared ($(\omega_t)^2$)	-0.0269	0.0050	-0.0300	0.0058	-0.0246	0.0076	-0.0126	0.0087
Shopping quality (μ_t)	0.0173	0.0075	0.0148	0.0085	0.0218	0.0077	0.0397	0.0109
Shopping quality squared ($(\mu_t)^2$)	-0.0009	0.0006	-0.0019	0.0007	-0.0023	0.0009	-0.0023	0.0011
Log of investment (i_{t-1})	0.0186	0.0068	0.0103	0.0075	0.0159	0.0075	0.0314	0.0073
Log of capital (k_{t-1})	0.1780	0.0105	0.1702	0.0170	0.1919	0.0141	0.1814	0.0163
Log of inventories (n_t)	-0.4358	0.0139	-0.4009	0.0239	-0.4580	0.0234	-0.4972	0.0206
Log of population (pop_t)	0.0175	0.0206	0.0487	0.0214	0.0477	0.0212	0.0253	0.0244
Log of pop. density ($popdens_t$)	0.0501	0.0123	0.0248	0.0113	0.0379	0.0129	0.0687	0.0124
Log of income (inc_t)	0.0379	0.1748	-0.0102	0.1631	0.3313	0.1656	0.1313	0.1821
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	

NOTE: Inventory turnover is defined as the cost of goods sold over average inventory. The intercept and average wage are included in all regressions. Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Table 8: Market size and the impact of rivals on inventory turnover, inventory, the number of product categories, and market share

	Inventory end year		Inventory turnover		No. of product categories		Market share	
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Panel A: Small local markets								
Productivity (ω_t)	0.1194	0.0516	0.2721	0.0631	1.7785	0.2117	0.0048	0.0216
Productivity squared ($(\omega_t)^2$)	-0.0130	0.0074	-0.0251	0.0090	0.0844	0.0303	0.0056	0.0031
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.2258	0.0225	-0.0228	0.0275	-0.1262	0.0924	0.0338	0.0094
Prod. *Rivals prod. ($\omega_t * \sum_{k\neq i}\omega_{kt}$)	0.0544	0.0042	-0.0072	0.0051	0.0039	0.0173	0.0017	0.0017
Shopping quality (μ_t)	0.0589	0.0111	-0.0361	0.0135	-0.4673	0.0455	0.0684	0.0046
Shopping quality squared ($(\mu_t)^2$)	-0.0039	0.0011	0.0030	0.0013	0.0392	0.0045	-0.0045	0.0004
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	-0.0408	0.0091	0.0340	0.0110	0.0565	0.0371	-0.0205	0.0038
Sh. quality*Rivals sh. quality ($\mu_t \sum_{k\neq i}\mu_{kt}$)	0.0028	0.0015	-0.0043	0.0019	0.0012	0.0064	0.0010	0.0006
Log of investment (i_{t-1})	0.0099	0.0106	0.0006	0.0130	0.1117	0.0436	-0.0027	0.0044
Log of capital (k_{t-1})	0.1106	0.0167	0.2553	0.0205	0.3205	0.0687	0.0038	0.0070
Log of inventories (n_t)	0.6829	0.0254	-0.5000	0.0310	-0.2506	0.1041	0.0461	0.0106
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	
Adjusted R-squared	0.934		0.518		0.516		0.531	
Panel B: Large Local markets								
Productivity (ω_t)	0.2034	0.0465	0.2072	0.0432	0.4398	0.1775	0.0985	0.0169
Productivity squared ($(\omega_t)^2$)	0.0155	0.0062	-0.0269	0.0057	-0.0498	0.0236	0.0087	0.0022
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.0248	0.0085	0.0073	0.0078	-0.0654	0.0324	0.0219	0.0030
Prod. *Rivals prod. ($\omega_t * \sum_{k\neq i}\omega_{kt}$)	0.0032	0.0012	0.0014	0.0011	-0.0149	0.0047	0.0014	0.0004
Shopping quality (μ_t)	0.0367	0.0076	0.0355	0.0070	-0.3692	0.0291	0.0843	0.0027
Shopping quality squared ($(\mu_t)^2$)	-0.0016	0.0007	0.0004	0.0007	0.0246	0.0030	-0.0054	0.0002
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	-0.0203	0.0049	-0.0157	0.0046	0.0742	0.0189	-0.0021	0.0018
Sh. quality*Rivals sh. quality ($\mu_t \sum_{k\neq i}\mu_{kt}$)	-0.0016	0.0005	-0.0015	0.0004	0.0096	0.0020	0.0012	0.0001
Log of investment (i_{t-1})	0.0400	0.0076	0.0400	0.0071	0.0449	0.0291	0.0007	0.0027
Log of capital (k_{t-1})	0.1260	0.0113	0.1561	0.0105	0.3118	0.0434	-0.0035	0.0041
Log of inventories (n_t)	0.7049	0.0150	-0.4459	0.0139	-0.0168	0.0573	0.0139	0.0054
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	
Adjusted R-squared	0.944		0.667		0.360		0.730	

NOTE: Inventory turnover is defined as the cost of goods sold over the average inventory. All regressions include an intercept and control for average wage and income. Productivity and shopping quality are estimated using the two-step estimation method described in Section 2.

Table 9: Counterfactual experiments: Changes in inventory, number of products, inputs and consumer surplus

	After 1 year		After 3 years		After 5 years	
	Mean	IQR	Mean	IQR	Mean	IQR
CF_1: The impact of positive shocks to productivity						
Inventory turnover	1.779	0.571	2.397	0.676	2.621	0.750
Number of products	1.230	0.987	1.745	1.074	1.981	1.344
Number of employees	1.484	0.201	4.663	1.305	9.465	3.569
Investment in technology	3.051	1.023	10.088	3.720	19.106	9.165
Inventory end of year	0.747	0.222	3.495	1.154	7.903	3.275
Consumer surplus	0.979	2.322	1.403	2.370	1.903	3.192
CF_2: The impact of positive shocks to productivity and reducing uncertainty of shopping quality						
Inventory turnover	2.332	1.338	5.551	2.330	7.294	3.451
Number of products	-0.083	2.348	-6.131	5.892	12.346	7.889
Number of employees	2.118	1.229	11.420	5.266	29.522	12.777
Investment in technology	3.374	1.042	13.654	4.500	30.300	11.443
Inventory end of year	1.413	1.276	11.843	6.925	35.285	18.093
Consumer surplus	0.089	7.422	-3.157	13.870	1.621	19.322
CF_3: The impact of positive shocks to demand						
Inventory turnover	0.337	0.240	0.240	0.358	-0.048	0.344
Number of products	-0.841	0.661	-1.720	1.025	-2.188	1.038
Number of employees	0.446	0.257	1.502	1.147	2.964	2.237
Investment in technology	0.086	0.127	0.251	0.606	0.876	1.430
Inventory end of year	0.458	0.269	2.122	1.518	4.547	3.234
Consumer surplus	2.736	6.231	5.298	9.013	6.788	12.726
CF_4: The impact of reducing uncertainty in productivity shocks and positive shopping quality						
Inventory turnover	0.619	1.395	0.596	2.005	0.035	2.324
Number of products	-0.782	1.140	-2.261	1.709	-3.774	2.066
Number of employees	0.201	1.163	-1.522	4.084	-8.511	11.203
Investment in technology	-1.142	2.331	-8.884	9.083	27.356	25.530
Inventory end of year	0.191	0.655	-0.547	3.384	-5.350	10.231
Consumer surplus	2.797	6.242	4.884	8.461	4.995	11.240

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90 - Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as above and below the median of the population.

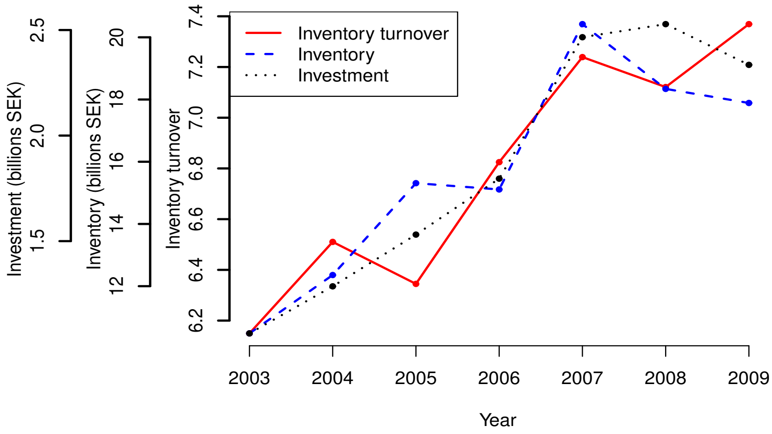


Figure 2: The evolution of inventory and investment in Swedish retail

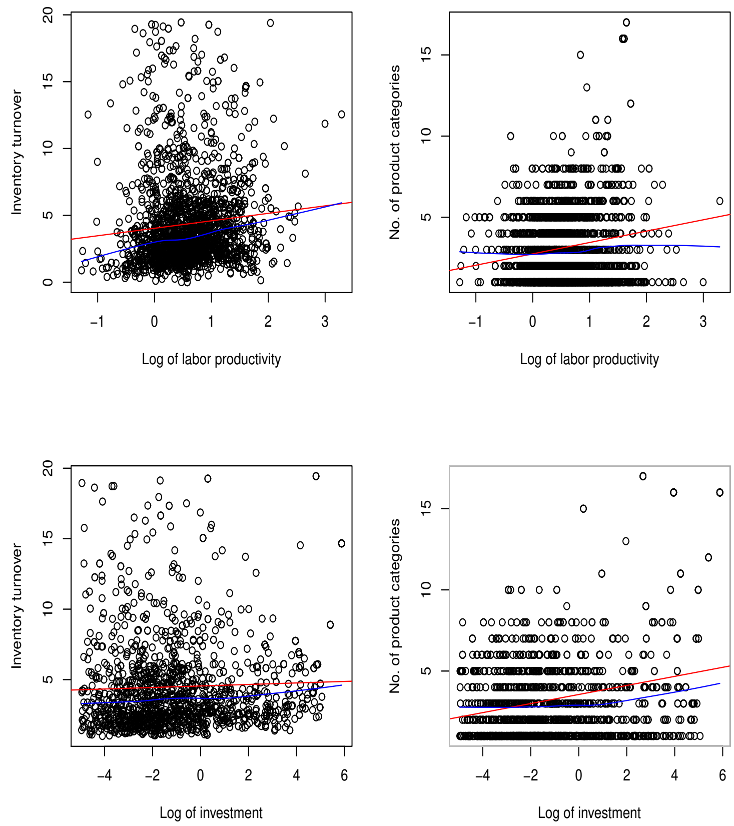


Figure 3: Scatter plots: The relationships between inventory turnover, the number of product categories, labor productivity, and investments

Online Appendix: Inventory Behavior, Demand, and Productivity in Retail

Florin Maican[1] and Matilda Orth[2]

Appendix A: A stylized model: The relationship between store productivity and inventory performance

This appendix section presents a stylized model that shows the relationship between store productivity and inventory performance and highlights key factors that affect the changes in inventory performance (i.e., dynamics).

The total sales-generating function y_{jt} (in logs) for store j is given by

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt} + \omega_{jt} + u_{jt}, \tag{8}$$

where l_{jt} is log of the number of employees; k_{jt} is log of capital stock; a_{jt} is log of the sum of inventory at the beginning of the period (n_{jt}) and the products bought during period t; ω_{jt} is total factor productivity based on sales data (TFPR), i.e., revenue productivity; and u_{jt} are i.i.d. shocks to sales. It is well documented that there is high persistence in productivity over time in a given store (Ackerberg et al., 2007; Syverson, 2011). For illustrative purposes, we assume that productivity ω_{jt} follows a simple $AR(1)$ process, i.e., $\omega_{jt} = \rho\omega_{jt-1} + \xi_{jt}$, where ρ is a coefficient capturing the persistence in store productivity, and ξ_{jt} are i.i.d. innovation shocks to productivity. The shocks ξ_{jt} provide information about uncertainty in productivity changes due to external or internal factors that are not under the control of the manager, for example, shocks related to the information technology system inside the store and logistics, shocks related to changes in regulation.

The goal of the stylized model is to provide a link between the common measures of inventory performance, such as inventory turnover and a store's total factor productivity. We define the log of inventory turnover in period t after the realization of sales as $it_{jt} = y_{jt} - n_{jt+1}$, where n_{jt+1} is the inventory at the beginning of period $t+1$ (end of period t) after sales are realized.[3] Using the sales generating function (8), the productivity process, and the inventory turnover equations, we derive a simple dynamic equation for inventory turnover

$$\begin{aligned} it_{jt} = \quad & \rho it_{jt-1} + \beta_l(l_{jt} - \rho l_{jt-1}) + \beta_k(k_{jt} - \rho k_{jt-1}) + \beta_a(a_{jt} - \rho a_{jt-1}) \\ & -(n_{jt+1} - \rho n_{jt}) + \xi_{jt} + u_{jt} - \rho u_{jt-1}. \end{aligned} \tag{9}$$

Managerial implications. The simple stylized model highlights that inventory turnover and productivity have several important implications for managers. First, equation (9) shows that

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[3]In many empirical applications, average inventory is used to compute inventory turnover.

the productivity persistence coefficient ρ drives inventory turnover, i.e., the dynamics of productivity over time is a key determinant of inventory turnover. Therefore, the persistence in store productivity provides information about the persistence in inventory turnover. Recent studies on retail find an average persistence in store productivity of approximately 70-80 percent (Maican and Orth, 2017). Second, innovation shocks to productivity ξ_{jt} and to sales u_{jt} affect inventory turnover, which is important since innovation shocks ξ_{jt} provide information on uncertainty in store productivity and affect optimal inventory and input choices (labor and capital), and their effect cumulates over time. Therefore, managers can learn how uncertainty in store total factor productivity affects inventory performance by understanding the distribution of ξ_{jt}. If the innovation shocks ξ_{jt} have large variance, managers have to prevent negative consequences of large variance in inventory performance by implementing policies to increase the persistence in store productivity (for example, investments in technology, optimal labor-capital substitution, and the optimal choice of product variety). Third, adjustments in inventory and input choices (labor and capital) over time directly influence inventory turnover because the optimal changes in labor and capital affect store productivity and, therefore, inventory performance.

Our illustrative stylized model has several limitations and does not take key features of retail business into account. Therefore, we provide a structural framework that accounts for (i) the role of multi-product stores for store performance, that is, capturing product variety inside a store; (ii) the role of demand for inventory performance and a store's choices, i.e., how stores can use the information from consumer preferences for products to make optimal decisions. We estimate demand shocks that capture quality of the shopping experience. We allow stores to learn from demand to improve future productivity; (iii) endogenous total factor productivity, inventory, investments, and input choices; (iv) heterogeneity in stores' responses to productivity changes, that is, we allow for a nonlinear productivity process.[4] The two sources of unobserved store-level heterogeneity (i.e., productivity and demand shocks) affect a store's input choices and, ultimately, its performance.

Appendix B: Recovering productivity and shopping quality

The general labor demand and inventory functions that arise from stores' optimization problem are $\mathrm{l}_{jt} = \tilde{l}_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, w_{jt}, \mathbf{x}_{mt})$ and $\mathrm{a}_{jt} = \tilde{a}_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, w_{jt}, \mathbf{x}_{mt})$. To back out ω_{jt} and μ_{jt}, functions $\tilde{l}_t(\cdot)$ and $\tilde{a}_t(\cdot)$ must be strictly monotonic in ω_{jt} and μ_{jt}, which holds under mild regularity conditions of the dynamic programming problem (Pakes, 1994). Maican and Orth (2018) discuss in detail all these conditions required for invertibility. By inverting these policy functions to solve for ω and μ, we obtain $\omega_{jt} = f_t^1(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$ and $\mu_{jt} = f_t^2(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$, i.e., the productivity and exogenous shocks are non-parametric functions of the observed variables in the state space and the controls.

In our setting, the estimation of the service generating function (3) is in two-steps. In the first step, we isolate stores' shopping quality perceived by customers μ_{jt} using information about stores' market shares ms_{jt}, i.e., $ln(ms_{jt}) - ln(ms_{ot}) = \rho_{np} np_{jt} + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc_{mt}^2 + \mu_{jt} + \nu_{jt}$,

[4] Nonlinearities in productivity complicate the dynamics of inventory turnover compared to the illustrative example in equation (9) that is valid only if productivity follows an AR(1) process (e.g., Ackerberg et al., 2007).

according to equation (4). The use of another output measure apart from sales of product category, and the distinction between stores' market shares and sales of a category, are important for identification. Our model contains two unobserved shocks and two Markov processes. We show how this additional output equation helps to recover shopping quality separate from productivity and ensures the identification of the model.

By substituting the nonparametric inversion $f_t^2(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$ for μ_{jt} in (4), we obtain an estimate of $b_t(\cdot)$ (i.e., predicted market shares, $\hat{b}_t$, where $b_t(\cdot) = f_t^2(\cdot)$). This allows us to write the shocks μ_{jt} as a parametric function, i.e., $\mu_{jt} = \hat{b}_{jt} - \rho_{np} np_{jt} - \rho_{inc,1} inc_{jt} - \rho_{inc,2} inc_{jt}^2$, which will be treated as an input in the multi-output service generating function.

Inventories can increase from a higher μ_{jt} and more products in the store, i.e., a higher love-for-variety. New technologies such as bar codes, scanners and business systems affect inventory levels, and positive adjustments avoid stockouts and increase quality. Technological advances can benefit the existing number of products that the store has in its assortment, e.g., through faster product lines and a higher frequency of turnover. Importantly, however, higher store productivity creates incentives for stores to increase their product variety and increase their size.[5]

By substituting μ_{jt} (predicted) and ω_{jt} into (1), the service generating function becomes

$$y_{ijt} = -\alpha_y y_{-ijt} + \phi_t(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt}) + u_{ijt}, \tag{10}$$

where $\phi_t(\cdot) = \beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt} + \beta_x \mathbf{x}_{mt} + \omega_{jt} + \mu_{jt}$. The estimation of (10) using OLS and the polynomial expansion of order 2 yields an estimate of service output without service output shocks u_{ijt}, which gives us $\hat{\phi}_t$, which is used to obtain store productivity ω_{jt} as a function of the parameters, $\omega_{jt} = \hat{\phi}_{jt} - \beta_l l_{jt} - \beta_k k_{jt} - \beta_a a_{jt} - \beta_q y_{0t} - \beta_x \mathbf{x}_{mt} - (\hat{b}_{jt} - \rho_{np} np_{jt} - \rho_{inc,1} inc_{jt} - \rho_{inc,2} inc_{jt}^2)$. Then, we use the information from the Markov processes to obtain the shocks $(\xi_{jt} + u_{ijt})$ and $(\eta_{jt} + \nu_{jt})$ as functions of parameters, which are used to form the moment conditions as described in the main text.

[5] Viewing the number of products as a measure of store size is in line with Holmes (2001) and is unarguably reasonable when using yearly data such that stores have time to adjust storage places, shelf space, etc., to an increasing number of products. Note that we consider the intensive margin in terms of increasing store size.

Appendix C: Alternative measures of the inventory turnover

Table C.1 presents the impact of productivity and demand shocks on adjusted inventory turnover, defined as the residual in the inventory turnover regression when controlling for differences in gross margin, capital intensity, store size, and store size squares (Gaur et al., 2005). The figures show that the results in the main text remain robust (Table 7).

Table C.1: Determinants of adjusted inventory turnover in retail

			Quantile regression					
	OLS		Q25		Q50		Q75	
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	0.7170	0.0843	0.1397	0.0366	0.1893	0.0399	0.3406	0.0469
Productivity squared ($(\omega_t)^2$)	0.0158	0.0129	-0.0470	0.0066	-0.0316	0.0062	-0.0118	0.0065
Shopping quality (μ_t)	0.0762	0.0200	0.0170	0.0085	0.0340	0.0081	0.0375	0.0072
Shopping quality squared ($(\mu_t)^2$)	-0.0070	0.0018	-0.0017	0.0009	-0.0033	0.0008	-0.0028	0.0010
Log of investment (i_{t-1})	0.0328	0.0172	0.0082	0.0065	0.0115	0.0066	0.0226	0.0058
Log of capital (k_{t-1})	-0.0453	0.0275	0.0106	0.0128	-0.0019	0.0118	-0.0056	0.0090
Log of inventories (n_t)	-0.5843	0.0381	-0.3014	0.0233	-0.3169	0.0148	-0.3358	0.0140
Log of population (pop_t)	0.1764	0.0561	0.0045	0.0230	0.0484	0.0203	0.0446	0.0174
Log of pop. density ($popdens_t$)	0.0400	0.0327	0.0580	0.0139	0.0542	0.0119	0.0536	0.0115
Log of income (inc_t)	0.4970	0.4970	-0.0542	0.1440	0.1921	0.1493	0.2849	0.1612
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	

NOTE: Adjusted inventory turnover is defined as the residual in the inventory turnover regression when controlling for differences in the gross margin, capital intensity, store size, and store size squares (Gaur et al., 2005). The intercept and average wage are included in all regressions. Productivity and the demand shock are estimated using the two-step estimation method in Section 2.

Appendix D: Heterogeneity across markets: Alternative specification

Table D.2 shows the estimated the impact of the rivals' productivity and shopping quality on inventory turnover, the number of product categories, and market share, given that the impact remains constant, i.e., there is no heterogeneity in impact by adding a quadratic term. The estimated results of this specification are consistent with the results in the main text in the paper.

Table D.2: Market size and the impact of rivals on inventory turnover, the number of product categories and market share

	Inventory turnover		No. of product categories		Market share	
	Est.	Std.	Est.	Std.	Est.	Std.
Panel A: Small local markets						
Productivity (ω_t)	0.1999	0.0580	1.3295	0.1978	0.0069	0.0210
Productivity squared ($(\omega_t)^2$)	-0.0325	0.0085	0.0379	0.0291	0.0057	0.0031
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.0439	0.0091	-0.1687	0.0305	0.0170	0.0032
Shopping quality (μ_t)	-0.0298	0.0132	-0.4409	0.0446	0.0656	0.0047
Shopping quality squared ($(\mu_t)^2$)	0.0021	0.0012	0.0396	0.0042	-0.0042	0.0004
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	0.0138	0.0062	0.0130	0.0252	-0.0141	0.0026
Log of investment (i_{t-1})	0.0016	0.0128	0.0833	0.0422	-0.0008	0.0045
Log of capital (k_{t-1})	0.2476	0.0204	0.2239	0.0692	0.0048	0.0073
Log of inventories (n_t)	-0.4718	0.0293	-0.0691	0.1021	0.0376	0.0108
Year fixed-effect	Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes	
Adjusted R-squared	0.514		0.480		0.513	
Panel B: Large Local markets						
Productivity (ω_t)	0.2129	0.0420	0.4079	0.1767	0.0600	0.0172
Productivity squared ($(\omega_t)^2$)	-0.0249	0.0057	-0.0622	0.0238	0.0056	0.0023
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.0000	0.0043	0.0058	0.0184	0.0131	0.0018
Shopping quality (μ_t)	0.0335	0.0070	-0.3520	0.0299	0.0839	0.0029
Shopping quality squared ($(\mu_t)^2$)	-0.0005	0.0006	0.0300	0.0028	-0.0046	0.0002
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	-0.0058	0.0028	0.0080	0.0122	-0.0069	0.0011
Log of investment (i_{t-1})	0.0397	0.0071	0.0501	0.0308	0.0013	0.0030
Log of capital (k_{t-1})	0.1603	0.0105	0.2672	0.0471	-0.0026	0.0046
Log of inventories (n_t)	-0.4381	0.0138	-0.0337	0.0657	0.0038	0.0064
Year fixed-effect	Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes	
Adjusted R-squared	0.664		0.346		0.709	

NOTE: Inventory turnover is defined as the cost of goods sold over average inventory. All regressions include an intercept and control for average wage and income. Productivity and the demand shock are estimated using the two-step estimation method described in Section 4.

Appendix E: Alternative counterfactual experiments

An additional policy experiment CF_5 is presented in Table E.3. The fifth counterfactual experiment (CF_5) evaluates positive shocks to productivity to compensate for negative shopping quality. That is, we increase the mean of ξ_{jt} to 0.2 and decrease the mean of ν_{jt} to -0.05.

An increase in productivity and a decrease in shopping quality. CF_5 assumes that stores experience larger positive shocks to productivity than in CF_1, i.e., the shocks to productivity are four times larger than the negative shocks to demand. Similar to CF_1 and CF_2, stores expand the number of employees because of gains in productivity (Table E.3). Both investments and inventories increase (especially in the long-run, e.g., over 30 percent after five years). Compared to CF_1, inventory turnover grows more quickly on average than the increase in productivity shocks (e.g., 6.8 percent in the coming year, 9.4 percent after three years, and 10.5 percent after five years). The positive productivity shocks drive the increase in the number of product categories (5.7 percent in the coming year and 10.5 percent after five years). The average consumer surplus changes are similar to the ones in CF_1, but the interquartile range is larger in CF_5 (especially in the next year).

In summary, due to productivity improvements stores grow in size (labor) and expand their product categories. Consumers experience more product variety to compensate for the negative effect caused by the decrease in shopping quality μ (e.g., shopping quality, product quality).

Table E.3: Counterfactual experiment: Changes in inventory, number of products, inputs and consumer surplus

CF_5: The impact of positive shocks productivity to compensate negative shocks to shopping quality						
Inventory turnover	6.842	2.220	9.446	2.940	10.553	3.395
Number of products	5.756	4.543	8.844	4.757	10.506	5.628
Number of employees	5.542	0.676	17.80	5.189	37.527	15.142
Investment in technology	12.390	4.012	42.186	14.977	82.344	39.295
Inventory end of year	2.586	0.747	12.439	4.708	29.330	14.390
Consumer surplus	1.178	3.147	0.417	1.032	1.151	2.400

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90 - Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as above and below the median of the population.

E.1: Heterogeneity across markets

Table E.4 summarizes counterfactual changes for small and large markets. By increasing the impact of positive shocks to productivity (CF_1), on average, there are small differences between small and large markets. However, small markets have a larger interquartile range in labor and investment changes than large markets. The consumer surplus gains are higher in small markets in short run but not in the long run (after three years). In addition, large markets have a higher interquartile range of the consumer surplus measure than small markets (i.e., a high heterogeneity in consumer surplus across large markets).

Reducing uncertainty in shopping quality and increasing productivity shocks (CF_2) affect small and large markets differently in terms of market share and consumer surplus. Small markets have a lower dispersion in changes in the short run, but this dispersion is higher in small markets than in large markets in the long run due to stronger competition. Consumers benefit from the consumer surplus improvements in small markets in the short run, whereas the surplus drops in both small and large markets in the long-run. As mentioned previously, the drop in consumer surplus is caused by increased store specialization when uncertainty in demand decreases.

Raising shopping quality (CF_3) creates a difference between small and large markets even if the mean increase of these shocks is the same. The positive changes in inventory turnover, labor, and investment are higher in large markets than in small markets. In addition, stores tend to specialize more in large markets. On average, consumer surplus gains are higher in small markets than in large markets, but this rank changes in the long run. Again, large markets have a higher dispersion in the consumer surplus changes.

Reducing uncertainty in productivity and increasing shopping quality (CF_4) affect small and large markets differently in the short and long run. For example, on average, there is no difference in inventory turnover in small and large markets in the short run, but stores in small markets have a higher inventory turnover in the long run. As in CF_3, stores specialize more in large markets (a larger drop in the number of product categories). There is more hiring in the short-run in both types of markets, but stores decrease their labor force in the long run, with a larger magnitude for small stores. Overall, consumer surplus increases in both types of markets, and large markets have a larger interquartile range in surplus changes than small markets.

Raising productivity to compensate for a drop in demand in the CF_5 does not create large differences between small and large markets. The most important finding is that inventory turnover changes are higher in small markets than in large markets. The number of product categories grows more quickly in large markets than in small markets. In contrast, on average, stores in small markets hire relatively more than stores in large markets, i.e., local community expansion.

In summary, the policy experiments show that the trade-off between productivity and demand plays a key role in driving differences across markets. The results highlight that understanding heterogeneity in shopping quality is important for the observed difference across markets, even if productivity drives the changes. The effect of shopping quality is more complex since it affects the dynamics of productivity shocks.

Table E.4: Counterfactual experiments: Market size and changes in inventory, the number of products, inputs and consumer surplus

	After 1 year				After 3 years			
	Small markets		Large markets		Small markets		Large markets	
	Mean	IQR	Mean	IQR	Mean	IQR	Mean	IQR
CF_1: The impact of positive shocks to productivity								
Inventory turnover	1.788	0.588	1.772	0.558	2.474	0.645	2.341	0.656
Number of products	1.270	0.967	1.200	0.974	1.690	0.957	1.785	1.137
Number of employees	1.486	0.350	1.482	0.153	4.763	2.075	4.590	1.026
Investment in technology	3.063	1.784	3.042	0.778	10.329	6.223	9.916	3.056
Inventory end of year	0.749	0.387	0.745	0.169	3.565	1.974	3.445	0.966
Consumer surplus	1.228	1.815	0.801	5.250	1.099	1.937	1.622	3.206
CF_2: The impact of positive shocks to productivity and reducing uncertainty of shopping quality								
Inventory turnover	2.374	1.313	2.302	1.295	5.467	2.385	5.611	2.377
Number of products	-0.169	1.948	-0.021	2.562	-5.580	5.803	-6.526	5.742
Number of employees	2.156	1.106	2.091	1.272	11.324	5.060	11.489	5.460
Investment in technology	3.394	1.787	3.359	0.872	13.710	6.291	13.615	3.806
Inventory end of year	1.452	1.149	1.385	1.317	11.715	6.709	11.935	7.228
Consumer surplus	1.263	6.410	-0.752	8.151	-0.560	12.165	-5.017	17.308
CF_3: The impact of positive shocks to demand								
Inventory turnover	0.294	0.252	0.367	0.238	0.184	0.319	0.280	0.364
Number of products	-0.682	0.625	-0.955	0.546	-1.417	0.869	-1.937	0.846
Number of employees	0.389	0.257	0.486	0.234	1.280	0.995	1.661	1.049
Investment in technology	0.057	0.127	0.106	0.116	0.141	0.474	0.330	0.588
Inventory end of year	0.398	0.269	0.501	0.246	1.824	1.331	2.336	1.384
Consumer surplus	3.455	4.782	2.220	13.952	4.081	7.683	6.171	12.782
CF_4: The impact of reducing uncertainty in productivity shocks and positive shocks to shopping quality								
Inventory turnover	0.613	1.343	0.624	1.414	0.623	2.103	0.577	1.942
Number of products	-0.593	1.100	-0.918	1.142	-1.917	1.539	-2.508	1.634
Number of employees	0.171	1.132	0.222	1.165	-1.778	4.017	-1.338	4.087
Investment in technology	-1.119	2.268	-1.159	2.361	-9.248	8.887	-8.623	9.100
Inventory end of year	0.144	0.658	0.224	0.636	-0.893	3.443	-0.300	3.383
Consumer surplus	3.455	4.792	2.325	14.920	3.810	7.421	5.653	12.169
CF_5: The impact of positive shocks to productivity to compensate negative shocks to shopping quality								
Inventory turnover	6.924	2.379	6.782	2.123	9.818	3.028	9.180	2.862
Number of products	5.761	4.350	5.753	4.413	8.312	4.268	9.225	4.930
Number of employees	5.609	1.448	5.490	0.560	18.454	8.846	17.338	4.301
Investment in technology	12.469	7.242	12.334	2.990	43.350	25.598	41.350	12.611
Inventory end of year	2.657	1.594	2.536	0.621	13.041	8.351	12.008	3.824
Consumer surplus	1.452	2.356	0.981	6.792	0.392	0.650	0.435	1.123

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90-Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as below and above the median of the population.